A Hybrid Reasoning Approach for Activity Recognition Based on Answer Set Programming and Dempster–Shafer Theory

Fadi Al Machot, Heinrich C. Mayr and Suneth Ranasinghe

Abstract This chapter discusses a promising approach for multisensor-based activity recognition in smart homes. The research originated in the domain of active and assisted living, particularly in the field of supporting people in mastering their daily life activities. The chapter proposes (a) a reasoning method based on answer set programming that uses different types of features for selecting the optimal sensor set, and (b) a fusion approach to combine the beliefs of the selected sensors using an advanced evidence combination rule of Dempster–Shafer theory. In order to check the overall performance, this approach was tested with the HBMS dataset on an embedded platform. The results demonstrated a highly promising accuracy compared to other approaches.

1 Introduction

Active and assisted living (AAL) [31] aims at helping persons in mastering their daily life activities [18] by employing intelligent technical means to compensate for disabilities. One of the major issues of AAL systems is to recognize the behavior of a person (i.e., what the person is currently doing) robustly in order to be able to provide optimal support. Activity theory conceptualizes a person's behavior as activities that consist of series of simple events such as walking, running, pushing a button, and grabbing something.

Consequently, activity recognition systems use different types of sensors that extract low-level features from the environment. For a structured view on that envi-

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ronment, researchers define an aggregation of contexts according to the task context [22], the personal context, the environmental context, the social context, and the spatiotemporal context. These contexts have to be analyzed and interpreted in order to identify the current activity and subsequently the whole activity. For example, in smart home environments, it is common that different activities may share many similar sensors, e.g., preparing a meal and preparing a drink activities can share the same simple events such as entering the kitchen, opening the cupboard, and opening the fridge. Thus, such situations form a kind of uncertainty that can cause bad decisions.

In this chapter, an uncertainty handling approach that allows better decisions in such situations and that can be implemented in embedded platforms is presented. It has been performed within the realm of the Human Behavior Monitoring and Support[1] (HBMS) project [32], that aims at deriving support services from integrated models of abilities and episodic knowledge that an individual has had or has temporarily forgotten.

The chapter is organized as follows: Sect. 2 gives an overview of the state-of-the-art approaches and their limitations. Section 3 covers a wide range of uncertainty handling approaches. Section 4 explains the answer set programming paradigm. Section 5 discusses the overall architecture of our activity recognition system. Section 6 presents the obtained results and the overall performance evaluation. The chapter ends in Sect. 7 with a discussion about uncertainty handling with respect to the proposed approach. Finally, a conclusion is provided in Sect. 8.

2 Related Work

During the last decade, different approaches to human activity recognition under uncertainty have been reported. They can be classified into three major categories along with their underlying model types: knowledge-based context models, graphical models, and syntactic models. Figure 1 provides an overview of activity recognition approaches under uncertainty.

Knowledge-based context models use expressions and rules to describe context properties such as entities, their properties, and the relationship between them. To recognize complex human activities, for example, the Ontology Web Language (OWL) [1] and answer set programming (ASP) [2, 3] are used for ontology representation and knowledge base (KB) creation, respectively.

Graphical models are used to describe complex activities in a higher-level representation, e.g., Bayesian dynamic networks [46], hidden Markov models [49], Dempster–Shafer [29], conditional random fields (CRFs) [44], and Gaussian mixture models (GMM) [36].

Syntactic models describe real-world events by structuring them with the use of a set of production rules, e.g., rough set theory [45] and fuzzy logic [11]. The Ontology

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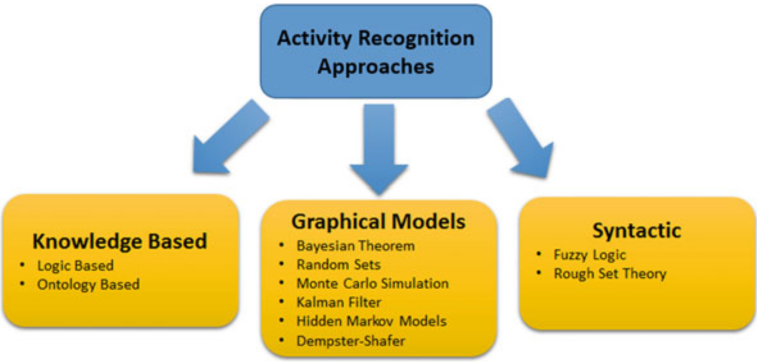

Fig. 1 An overview of complex event detection approaches under uncertainty

Web Language (OWL 2) is still a major research area [30, 35], and fortunately, OWL 2 ontologies are supported by a fuzzy logic-based reasoner to handle uncertainty.

Bayesian inference suffers from difficulty in defining a priori probabilities and the inability to consider general uncertainty [21]. Hidden Markov models (HMM) showed promising results in the field of activity recognition, but they do not perform perfectly, since human behavior is not Markovian [37]. The fuzzy logic sensor fusion method provides an effective means to handle requirements of human daily life [17]. However, fuzzy logic sensor fusion defines membership functions and production rules that are extremely domain- and problem-specific.

To overcome the limitations of the Bayesian inference method, the Dempster–Shafer method generalizes Bayesian theory to allow for distributing support not only to a single hypothesis but also to a union of hypotheses [23]. The Dempster–Shafer and Bayesian methods produce identical results when all the hypotheses are singletons (not nested) and mutually exclusive [4]. Additionally, the combination rule of the classical Dempster–Shafer theory can be implemented to fuse data from sensors, but it can lead to illogical results in the presence of highly conflicting evidence.

Therefore, we aim at a technique to propose a reasoning approach for activity recognition under uncertainty that (a) avoids the previous limitations, (b) responds in real time, (c) runs on embedded platforms, and (d) uses an evidence combination rule [4] that delivers logical results even in the presence of highly conflicting evidence.

3 Approaches to Uncertainty Handling

There is a variety of approaches for handling uncertainty in activity recognition. Since we will present a novel approach to this topic subsequently within this chapter, this section discusses the state of the art within that field.

Bayesian approach: A probabilistic distribution expressing data uncertainty was the first approach to handling the problem of imperfect data. Later, new techniques appeared that dealt with the limitations of probability theory, such as fuzzy set theory and evidential reasoning. Many event detection approaches require prior knowledge of the cross covariance of data to perform well. Unfortunately, prior knowledge can be affected by different sources of noise in the observation environment. The Bayesian inference network offers the following advantages: it incrementally estimates the probability of the truth of a hypothesis for new given observations; reasoning can be incorporated using prior knowledge about the likelihood of a hypothesis being true; and when empirical datasets are not available, it allows using subjective probability estimators to estimate the prior of hypotheses. Although Bayesian networks have these advantages, Bayesian reasoning also has some disadvantages [20] in that it suffers from the difficulty in finding prior probabilities, from complexities when there are multiple hypotheses and multiple conditionally dependent events, and from the inability to account for general uncertainty. Dynamic Bayesian networks [33] are suitable for the consideration of temporal aspects. They represent state variable changes over time. Moreover, Kalman filtering [47] is an optimal solution for estimating the moments of a probabilistic distribution that uses a series of measurements observed over time containing inaccuracies, uncertainties, and noise.

Hidden Markov models: Simple hidden Markov models (HMM) can be used to model simple events to detect complex events, but they do not support modeling temporal aspects. They offer the possibility to model temporal granularity, which is not possible with a simple HMM. Therefore, to solve this problem, layered HMMs offer this possibility.

Dynamic Bayesian networks (DBN) offer more flexibility in representing relationships between activities and subactivities, but some problems could arise when the system is detecting complex events that might be solved using tractable variational algorithms. DBN is a generalization of HMMs and CRFs. It supports modeling complex relationships between variables over time. However, this can affect the reasoning process. Tractable variational algorithms can help to eliminate this effect [7].

Fuzzy logic: Fuzzy set theory deals with vagueness of data, and evidential belief theory focuses on both uncertain and ambiguous data. However, a disadvantage of fuzzy logic is that it cannot be the main fusion method in a generalizable architectural solution to design a context-aware computing system. Moreover, fuzzy set membership function assignment and production rules are usually extremely domain- and problem-specific, making it difficult to implement the method as a general approach.

Dempster–Shafer: Dempster–Shafer theory performs well only under situations of minimal conflict or irrelevant conflict in which all sources are considered reliable [39]. Because of such limitations, new approaches have been developed, for example, the new version of DSET called the transferable belief model (TBM) [40] and DezertSmarandache theory (DSmT) [12]. The transferable belief model (TBM) theory extends DSET by DSmT, which allows the combination of all types of independent sources to be represented as belief functions, but it is specifically focused on the fusion of uncertain, highly conflicting sources of evidence. Moreover, the combination rule of the classical Dempster–Shafer theory can be implemented to fuse data from two sensors, but it can lead to illogical results in the presence of highly conflicting evidence. However, researchers in [4] proposed an evidence combination rule to provide more realistic results than those offered by the standard Dempster–Shafer combination rule. In order to perform event detection successfully, in the case of fusing sensors that do not require preliminary or additional information such as data distribution or a membership function, rough set theory is suitable [24].

Random sets and Monte Carlo simulation-based techniques: The conditional random fields technique models the conditional probability of observations for better class discrimination. A key advantage of CRFs is that they offer the possibility to include a wide variety of arbitrary nonindependent features of the input [28]. CRFs have been compared to HMMs for activity recognition. In general, they show better results than HMMs [43]. However, they need more computation time, especially if the low-level features are large. Several solutions have been suggested for optimizing the training of conditional random fields for event detection such as gradient tree boosting [13].

Furthermore, the Monte Carlo simulation-based techniques such as sequential Monte Carlo (SMC) and Markov chain Monte Carlo (MCMC) are among the most powerful approaches to approximating probabilities. Particle filters are a recursive implementation of the SMC algorithm [19]. They provide an alternative for Kalman filtering in dealing with non-Gaussian noise and nonlinearity in the system. They assign weights to the randomly chosen samples (particles) to approximate the probability density. Particle filters can be used in the framework of event detection to increase the performance of Bayesian approaches.

Ontologies and logic Based: Ontologies and logic-based event detection approaches are a tentative solution to performing complex reasoning tasks. The current frequently used ontology language is the Ontology Web Language (OWL 2), which has recently become a W3C recommendation for ontology representation [15]. Therefore, several fuzzy extensions of description logics can be found in the literature [27], and some fuzzy DL reasoners have been implemented, e.g., fuzzyDL [8] and Fire [42]. Each reasoner uses its specific fuzzy description logic (DL) language to model the fuzzy ontologies. Therefore, there is a need for a standard way to represent such information.

Logic-based approaches that use hidden Markov models, Bayesian networks, or conditional random fields typically encode only pairwise event constraints, and therefore, they take time points as primitives of their models. Consequently, many types of events are fundamentally interval-based and are not accurately modeled in terms of time points [10].

Hybrid approaches: Hybrid approaches combine components (methods) of complex event detection to gain the advantages of each approach. Some hybrid event detection approaches, e.g., the hybridization of fuzzy set theory with D-S evidence theory, have been studied frequently [48].

A combination of fuzzy set theory with rough set theory (FRST), proposed by Dubois and Prade, is another important theoretical hybridization that has appeared in the literature [14]. Application of FRST to complex event detection in visual surveillance systems has not often been investigated, since rough set theory itself is still not an established data event detection approach under uncertainty.

4 Answer Set Programming (ASP)

Answer set programming (ASP) [6, 9] is widely used in artificial intelligence (AI0). It is recognized as a powerful tool for knowledge representation and reasoning, especially due to its high expressiveness and ability to deal with incomplete knowledge.

ASP programs consist of two major parts: the knowledge base part, in which the facts are included, and the rules part, which describes how the problem should be solved. The output of ASP systems is the answer sets (models) that present the possible solutions of the encoded problem. Figure 2 shows the overall steps for solving problems using ASP.

An ASP program formulated in the language of AnsProlog (also known as A-Prolog) is a set of rules of the form

$$a_0 \leftarrow a_1, \ldots, a_m, \neg a_{m+1}, \ldots, \neg a_n, \tag{1}$$

where $1 \leq m \leq n$, and each a_i is an atom of some propositional language. Here $\neg a_i$ is a negation-as-failure literal (naf-literal). Given a rule of this form, the left- and right-hand sides are called head and body, respectively.

A rule may have either an empty head or an empty body, but not both. Rules with an empty head are called constraints; rules with an empty body are called facts.

Let X be a set of ground atoms in a given ASP program, i.e., all atoms that do not have free variables; as such, X is the Herbrand base of that ASP program. Then the body in a rule of the form (1) is satisfied by X if $\{a_{m+1}, \ldots, a_n\} \cap X = \phi$ and $\{a_1, \ldots, a_m\} \subseteq X$. A rule with a nonempty head is satisfied by X if either $a_0 \in X$ or its body is not satisfied by X. A constraint is satisfied by X if its body is not satisfied by X.

Many facts from the state of the art [5, 25, 41] made ASP one of the most powerful knowledge representation paradigms, due to its strong expressive ability to model and represent many classical problems of knowledge representation. Although defeasible information cannot simply be represented easily, ASP offers the use of default negation in the body of rules, which makes it conceivable.

Furthermore, conditions allow for instantiating variables for collections of terms within a single rule. This is particularly useful for encoding conjunctions or disjunctions over arbitrarily many ground atoms, as well as for the compact representation of aggregates. Additionally, optimization in ASP is indicated via maximization and minimization statements that can extend a basic question whose answer set can be upgraded to an optimal one.

Fig. 2 Problem-solving steps using ASP

5 Reasoning Process Structure

This section describes the process structure of the proposed approach. It consists of two major phases: (1) an offline phase for analyzing and windowing the streaming data, and (2) an online phase to recognize activities using the same windowing technique.

We exploit the advantages of ASP to optimize extracted features from sensor streams. The goal of the optimization is to help in assigning weights to the online sensor streams with respect to their priorities.

Consequently, the concept is to maximize the total combined beliefs of those candidates (see Fig. 3). To evaluate the overall performance, we apply our approach to the HBMS dataset. This set consists of data from 22 sensors (switches and motion sensors).

Each sensor generates binary output only, 1 if it is activated, 0 otherwise. The dataset is annotated with five activities such as watching TV, going shopping, checking blood pressure, getting a drink, and preparing a meal. None of these activities occur simultaneously. Due to the binary nature of sensors, context values for these sensors provide simple events if dishes or cups are taken, devices are turned on or off. The lab had three virtual rooms (a living room, a kitchen, and a bedroom).

Activities were recorded over 18 days in the HBMS lab. The actors performed different activities over two hours, distributed over three activity periods per day.

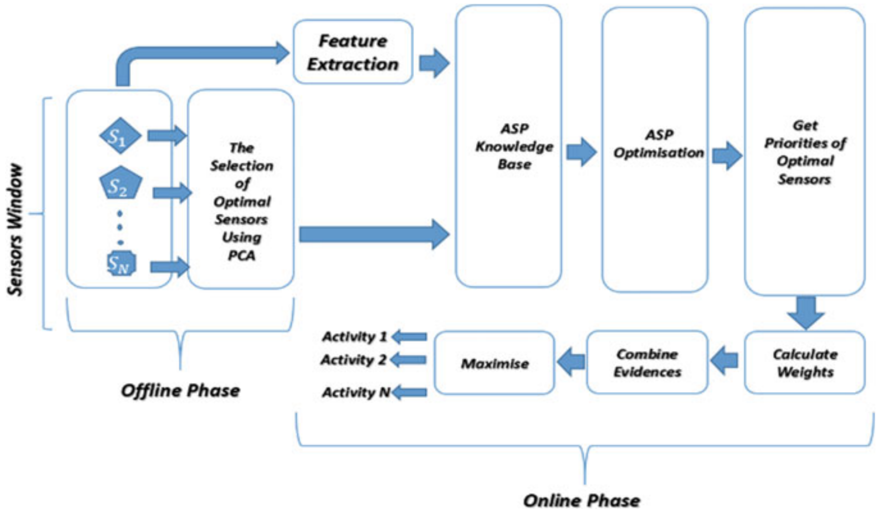

Fig. 3 Process structure of the activity recognition approach

5.1 *Offline Phase*

The basic concept of the offline phase is to analyze the dataset based on different features to find the optimal number of activated sensors. In order to employ efficient approach, we extracted the following features within two to three days of the given dataset: (a) the number of activations of each sensor, (b) the duration time of each sensor activation, (c) the duration time of each activity, (d) the time of performance of each activity, (e) the number of activated sensors for each activity, and (f) the location of the sensor.

The analysis is applied using information gain (IG) attribute evaluation [34]. The results showed that the number of activations for each sensor was the most relevant attribute.

Consequently, for each activity, we sorted the sensors based on their activation times and started out by choosing the first three, four, five, and six sensors in the window as optimal sensors.

Hence, using the support vector machine (SVM) based attribute ranking approach [16], we chose the window whose optimal number of sensors delivered the highest rank.

5.2 *Online Phase*

After the optimal sensors for each activity have been determined, the sensor data is collected in a window until the optimal sensors of one activity are activated (thus, the provided dynamic window size avoids the previously mentioned disadvantages). As soon as this happens, the following three steps are applied: (a) assignment of priority levels to each optimal sensors, (b) adjustment of sensors' belief, and (c) evidence combination of optimal sensors' beliefs.

5.2.1 ASP Optimization to Assign Priority Levels to Sensors

The assignment of priority levels is calculated based on three different features, which are categorized as follows: (1) the number of activations of each optimal sensor (which is the result of the offline phase); (2) the cost value, which is the performance of the measurement for each optimal sensor; (3) the sensor activation time. Consequently, sensors are represented in our knowledge base as follows:

```
sensor(Id).
sensor_time(SensorId,Time).
hist_importance(SensorId,ImportanceValue).
cost(SensorId,CostValue).
timing(SensorId,Duration).
```

```
user_current_time(Time).
```

The cost value (costValue) per optimal sensor is calculated as $1 - CV$, where the confidence value (CV) is the performance of the measurement for each optimal sensor. The importance value (`hist_imprtance`) is defined as the number of activations of each optimal sensor in the current window divided by the total number of activations. See Eqs. 2 and 3, where N is the total number of optimal sensors in the window, i is the index of the sensor in the window, $AllAct$ is the sum of all activations in the window, and s_k is the current sensor:

$$hist\_importance(s_k) = \frac{1}{AllAct} \sum_{i=1}^{N} f(s_{k_i}) \tag{2}$$

$$f(s_{k_i}) = \begin{cases} 1, & \text{if } s_k \; is \; ON, \\ 0, & \text{if } s_k \; is \; OFF. \end{cases} \tag{3}$$

Timing is considered with respect to the firing time of each optimal sensor. This feature is specified in the offline phase. Based on this, an optimization problem is to be solved using ASP and considering our three priority factors (in ascending order), identified by @:

```
1. maximize[sensor(X): hist_importance (X,Y)=Y @3].
2. minimize[sensor(X): cost (X,Y):
hist_importance (X,Z)=Y/Z @1].
3. maximize{sensor(X): timing (X,Y)=Y @2}.
```

Lines 1–3 contribute to optimization statements in descending order of significance. The optimization statement (line 1) gives the first priority to `hist_importance`, which should be maximized. Line 2 serves to minimize the cost of each optimal sensor, which has the last priority. Line 3 states that timing is our second priority, which should be maximized. The statements `maximize` and `minimize` are predefined optimization statements that are provided by ASP.

5.2.2 The Adjustment of Sensor Belief

After reading sensor data in the window, each sensor defines its belief (propagates) across the context values for the sensor via a mass function. The adjustment of sensors' belief is considered with respect to sensors' priority, which results from the sensor occurrence sequence in the answer set. Consequently, evidence propagation from context values is achieved using compatibility relations and evidential mapping [26, 29].

For illustration, at time t, the sensor mass functions produce "GetDrink," where θ is the frame of discernment:

$\{FridgeUsed = 1, notFridgeUsed = 0\} \rightarrow$
$\{GetDrink = 1, notGetDrink = 0\}$,
$\{CupUsed = 0, notCupUsed = 1\} \rightarrow$
$\{GetDrink = 0, notGetDrink = 0.8, \theta = 0.2\}$

"Prepare a meal," where θ is the frame of discernment:

$\{FridgeUsed = 1, notFridgeNotUsed = 0\} \rightarrow$
$\{Prepareameal = 1 notPrepareameal = 0\}$,
$\{MicrowaveUsed = 1, MicroUsed = 0\} \rightarrow$
$\{Prepareameal = 0.2, notPrepareameal = 0, \theta = 0.8\}$
$\{PlateUsed = 1, notPlatesUsed = 0\} \rightarrow$
$\{Prepareameal = 1, notPrepareameal = 0\}$,
$\{GroceriesUsed = 0, notGroceriesUsed = 1\} \rightarrow$
$\{Prepareameal = 1, notPrepareameal = 0\}$

After setting the priorities for each sensor, Eq. 4 is used to adjust the belief of each optimal sensor, where W is the weight of the sensor, Pr is the priority of the sensor, s_i is the current sensor, and Mu is the number of optimal sensors.

For example, in case of $Mu = 5$, the weights will be assigned as follows: the sensor with first priority will be weighted by 1, the sensor with second priority will be weighted by 0.80, the third by 0.60, the fourth by 0.40, and the fifth by 0.2:

$$W(s_i) = \frac{((Mu - Pr(s_i)) + 1)}{Mu}. \tag{4}$$

5.2.3 Evidence Combination

Dempster–Shafer theory can effectively represent uncertain and imprecise information. It has been widely used in the field of information fusion. But in multimodal sensor networks, there are often conflicting sensor reports due to the interference of the natural environment or other reasons.

It has been proven that classical Dempster–Shafer evidence theory cannot deal with the integration of conflict information effectively. If Dempster's combination rule is used directly to integrate evidence, with such conflicting cases, the results do not reflect reality. Many improved methods have been proposed to combine evidence.

As an example, Ali et al. [4] proposed a combination method by complementing the multiplicative strategy by an additional strategy. This method shows promising results for evidence combinations in comparison to other existing approaches.

The major components of evidence theory proposed by Dempster–Shafer are the frame of discernment θ and the basic probability assignment (BPA). The frame of discernment θ is the power set of the set of all possible mutually exclusive hypotheses (at most one of which is true), i.e., in our case, the set of all possible events (in the sense of operation sequences). BPA is a function $m : 2^{\theta} \rightarrow [0, 1]$ related to a proposition satisfying conditions (1) and (2) [38] (see Eqs. 5 and 6):

$$m(\phi) = 0, \tag{5}$$

$$\sum_{A \in \theta} m(A) = 1. \tag{6}$$

Here, A is any element of the frame of discernment, and ϕ refers to the empty set. Consequently, the whole body of evidence of one sensor is the set of all basic probability assignments greater than 0 under one frame of discernment.

The combination of multiple evidence defined in the same frame of discernment is a combination of the confidence level values based on the basic probability assignments (BPA). If there are two sensors, where each sensor has its body of evidence ms_1 and ms_2, these bodies of evidence are the corresponding BPA functions of the frame of discernment.

We have used the combination rule proposed by [4], since it provides more realistic results than the standard Dempster–Shafer rule when conflicting evidence from multiple sources is combined. Equation 7 shows how to calculate the combined probability assignment function:

$$m_{s_1} \oplus m_{s_1}(e) = \frac{1 - (1 - m_{s_1}(e)) * (1 - m_{s2}(e))}{1 + (1 - m_{s_1}(e)) * (1 - m_{s2}(e))}. \tag{7}$$

Equation 7 is used to combine all the beliefs of optimal sensors to maximize the occurrence of the best activity candidates, where m is the mass function, and e is the evidence.

6 Results Obtained

From the HBMS dataset, we extracted a subset consisting of 10-day observations including all five activities to determine the inference during the offline phase. The online phase was applied using the data from the other eight days. The proposed windowing technique was performed in both phases. In other words, the data is divided into 70% for training and 30% for testing.

Table 1 shows the results of our experiments with respect to accuracy and F-measure. Clearly, our overall accuracy is (96.76). Figure 4 shows the overall activity distribution in the dataset.

In order to measure the runtime behavior of the answer set programming approach, we performed several tests on an embedded platform: A pITX-SP[2] 1.6 plus board manufactured by Kontron. It was equipped with a 1.6-GHz Atom Z530 and 2 GB

[2]See http://www.kontron.de/.

Table 1 Overall performance C1: watch TV; C2: go shopping; C3: Check blood pressure; C4: get a drink; C5: prepare a meal

Class	Accuracy (%)	F-Measure (%)
C1	100	1
C2	95.4	0.94
C3	96.9	0.94
C4	91.3	0.89
C5	100	0.96

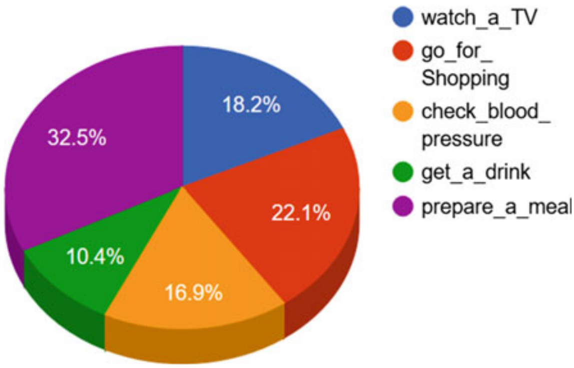

Fig. 4 Overall activity distribution as a percentage

RAM. For the evaluation, Clingo[3] was used as a solver for ASP. The average time to detect a complex event was 0.4 s.

7 Uncertainty Handling

Our approach convincingly shows that (a) it does not face the problem of the traditional Bayes's theorem for assigning the right priority probabilities, (b) it can respond in real time and run on embedded platforms, (c) it uses an evidence combination rule that can lead in the presence of highly convicting evidence to logical results, (d) ASP is an appropriate approach to dealing with incomplete knowledge and thus uncertainty. Little research has been proposed into the use of answer set programming (ASP) for reasoning under uncertainty in AAL environments.

The proposed approach can be used for any purposes simply by adjusting the knowledge base to the new context. This adjustment is not difficult, since only the facts have to be adapted but not the rules. ASP supports a number of arithmetic functions that are evaluated during grounding. Therefore, the major reasoning-under-uncertainty approaches can be implemented in ASP.

[3]See http://potassco.sourceforge.net/.

Also, different optimization problems have the same formulations to be represented as logic programs. Therefore, ASP provides this possibility using maximize and minimize statements. Additionally, the intuitive semantics of ASP programs avoid the complex representation of optimization problems that are based on other standard approaches, for instance simulated annealing, genetic algorithms, and artificial neural networks. Moreover, the syntax of logic programs offers the possibility of fast implementation of different complex problems that might be difficult to represent in any other form.

Furthermore, constraints play an important role in ASP, because adding a constraint to a logic program P affects the collection of stable models of P in a very simple way. It eliminates the stable models that violate the constraint. This feature can be applied to activity recognition by the definition of the constraints in the environment.

8 Conclusion

Activity recognition requires a detailed analysis and understanding of the domain in which the activities to be recognized occur. Within the scope of this chapter we have shown that combining logic programming (ASP) and Dempster–Shafer theory is a solid basis for implementing a powerful tool to detect complex activities. In particular, the ASP paradigm proved to be suitable for activity recognition systems due to its inherent knowledge representation and optimization capabilities. In addition, we were able to improve our technique's accuracy by assigning weights to sensor events with respect to different spatial and temporal features. Altogether, this concept allowed us to come up with a methodology that improves the handling of uncertainty. With respect to other approaches, a disadvantage of the one presented here is the fact that it needs previously collected knowledge about users and sensors. This chapter is mainly concerned with the development of effective activity recognition systems for complex event detection under uncertainty. It discusses the consideration of uncertainty in the framework of complex event detection involving multiple sensors. Moreover, we addressed diverse state-of-the-art approaches for complex event detection, the advantages and disadvantages of each technique, and a comprehensive evaluation about the performance of the methodologies for handling uncertainty. In our future work, we will test the proposed reasoning approach using other international datasets and increase the number of activities to be able to compare the proposed approach with other state-of-the-art approaches.

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References

1. Akdemir, U., Turaga, P., Chellappa, R.: An ontology based approach for activity recognition from video. In: Proceedings of the 16th ACM international conference on Multimedia, pp. 709–712. ACM (2008)
2. Al Machot, F., Kyamakya, K., Dieber, B., Rinner, B.: Real time complex event detection for resource-limited multimedia sensor networks. In: 2011 8th IEEE International Conference on Advanced Video and Signal-Based Surveillance (AVSS), pp. 468–473. IEEE (2011)
3. Al Machot, F., Tasso, C., Dieber, B., Kyamakya, K., Piciarelli, C., Micheloni, C., Londero, S., Valotto, M., Omero, P., Rinner, B.: Smart resource-aware multimedia sensor network for automatic detection of complex events (2011)
4. Ali, T., Dutta, P., Boruah, H.: A new combination rule for conflict problem of dempster-shafer evidence theory. Int. J. Energy Inf. Commun. **3**(1), 35–40 (2012)
5. Baral, C.: Knowledge Representation, Reasoning and Declarative Problem Solving. Cambridge University Press, Cambridge (2003)
6. Baral, C., Gelfond, G., Son, T.C., Pontelli, E.: Using answer set programming to model multi-agent scenarios involving agents' knowledge about other's knowledge. In: Proceedings of the 9th International Conference on Autonomous Agents and Multiagent Systems: volume 1-Volume 1, pp. 259–266. International Foundation for Autonomous Agents and Multiagent Systems (2010)
7. Beal, M.J.: Variational algorithms for approximate Bayesian inference. Ph.D. thesis, University of London (2003)
8. Bobillo, F., Straccia, U.: fuzzydl: an expressive fuzzy description logic reasoner. In: FUZZ-IEEE, pp. 923–930 (2008)
9. Brain, M., De Vos, M.: Answer set programming–a domain in need of explanation. In: Exact08: International Workshop on Explanation-aware Computing (2008)
10. Brendel, W., Fern, A., Todorovic, S.: Probabilistic event logic for interval-based event recognition. In: 2011 IEEE Conference on Computer Vision and Pattern Recognition (CVPR), pp. 3329–3336. IEEE (2011)
11. Chiang, S.-Y., Kan, Y.-C., Tu, Y.-C., Lin, H.-C.: Activity recognition by fuzzy logic system in wireless sensor network for physical therapy. In: Intelligent Decision Technologies, pp. 191–200. Springer (2012)
12. Dezert, J.: Foundations for a new theory of plausible and paradoxical reasoning. Inf. Secur. **9**, 13–57 (2002)
13. Dietterich, T.G., Ashenfelter, A., Bulatov, Y.: Training conditional random fields via gradient tree boosting. In: Proceedings of the twenty-first international conference on Machine learning, p. 28. ACM (2004)
14. Dubois, D., Prade, H.: Rough fuzzy sets and fuzzy rough sets*. Int. J. Gen. Syst. **17**(2–3), 191–209 (1990)
15. Grau, B.C., Horrocks, I., Motik, B., Parsia, B., Patel-Schneider, P., Sattler, U.: Owl 2: the next step for owl. Web Semant. Sci. Serv. Agents World Wide Web **6**(4), 309–322 (2008)
16. Guyon, I., Weston, J., Barnhill, S., Vapnik, V.: Gene selection for cancer classification using support vector machines. Mach. Learn. **46**(1–3), 389–422 (2002)
17. Jones, R.E., Connors, E.S., Endsley, M.R.: Incorporating the human analyst into the data fusion process by modeling situation awareness using fuzzy cognitive maps. In: 12th International Conference on Information Fusion, 2009. FUSION'09, pp. 1265–1271. IEEE (2009)
18. Katz, S.: Assessing self-maintenance: activities of daily living, mobility, and instrumental activities of daily living. J. Am. Geriatr. Soc. **31**(12), 721–727 (1983)
19. Khaleghi, B., Khamis, A., Karray, F.O., Razavi, S.N.: Multisensor data fusion: a review of the state-of-the-art. Inf. Fusion **14**(1), 28–44 (2013)
20. Klein, L.A.: Sensor and Data Fusion Concepts and Applications. Society of Photo-Optical Instrumentation Engineers (SPIE), Bellingham (1999)
21. Klein, L.A.: Sensor and Data Fusion: A Tool for Information Assessment and Decision Making, vol. 324. Spie Press, Bellingham (2004)

22. Kofod-Petersen, A., Cassens, J.: Using activity theory to model context awareness. In: Modeling and Retrieval of Context, pp. 1–17. Springer (2006)
23. Kohlas, J., Monney, P.-A.: A Mathematical Theory of Hints: An Approach to the Dempster-Shafer Theory of Evidence, vol. 425. Springer Science & Business Media, Berlin (2013)
24. Liang-zhou, C., Wen-kang, S., Yong, D., Zhen-fu, Z.: A new fusion approach based on distance of evidences. J. Zhejiang Univ. Sci. A **6**(5), 476–482 (2005)
25. Lifschitz, V.: Answer set programming and plan generation. Artif. Intell. **138**(1), 39–54 (2002)
26. Lowrance, J.D., Garvey, T.D., Strat, T.M.: A framework for evidential-reasoning systems. In: Classic Works of the Dempster-Shafer Theory of Belief Functions, pp. 419–434. Springer (2008)
27. Lukasiewicz, T., Straccia, U.: Managing uncertainty and vagueness in description logics for the semantic web. Web Semant. Sci. Serv. Agents World Wide Web **6**(4), 291–308 (2008)
28. McCallum, A.: Efficiently inducing features of conditional random fields. In: Proceedings of the Nineteenth conference on Uncertainty in Artificial Intelligence, pp. 403–410. Morgan Kaufmann Publishers Inc. (2002)
29. McKeever, S.: Recognising situations using extended Dempster-Shafer theory. Ph.D. thesis, National University of Ireland, Dublin (2011)
30. Meditskos, G., Dasiopoulou, S., Kompatsiaris, I.: Metaq: a knowledge-driven framework for context-aware activity recognition combining sparql and owl 2 activity patterns. Pervasive Mob. Comput. (2015)
31. Menschner, P., Prinz, A., Koene, P., Köbler, F., Altmann, M., Krcmar, H., Leimeister, J.M.: Reaching into patients homes-participatory designed aal services. Electron. Mark. **21**(1), 63–76 (2011)
32. Michael, J., Grießer, A., Strobl, T., Mayr, H.C.: Cognitive modeling and support for ambient assistance. In: Information Systems: Methods, Models, and Applications, pp. 96–107. Springer (2012)
33. Murphy, K.P.: Dynamic bayesian networks: representation, inference and learning. Ph.D. thesis, University of California (2002)
34. Novakovic, J.: Using information gain attribute evaluation to classify sonar targets. In: 17th Telecommunications Forum TELFOR, pp. 24–26 (2009)
35. Okeyo, G., Chen, L., Wang, H., Sterritt, R.: Dynamic sensor data segmentation for real-time knowledge-driven activity recognition. Pervasive Mob. Comput. **10**, 155–172 (2014)
36. Piyathilaka, L., Kodagoda, S.: Gaussian mixture based hmm for human daily activity recognition using 3d skeleton features. In: 2013 8th IEEE Conference on Industrial Electronics and Applications (ICIEA), pp. 567–572. IEEE (2013)
37. Pruteanu-Malinici, I., Carin, L.: Infinite hidden markov models for unusual-event detection in video. IEEE Trans. Image Process. **17**(5), 811–822 (2008)
38. Rice, J.: Mathematical Statistics and Data Analysis. Cengage learning, Boston (2006)
39. Sentz, K., Ferson, S.: Combination of Evidence in Dempster-Shafer Theory, vol. 4015. Citeseer (2002)
40. Smets, P.: The combination of evidence in the transferable belief model. IEEE Trans. Pattern Anal. Mach. Intell. **12**(5), 447–458 (1990)
41. Soininen, T.: An Approach to Knowledge Representation and Reasoning for Product Configuration Tasks. Finnish Academies of Technology, Espoo (2000)
42. Stoilos, G., Simou, N., Stamou, G., Kollias, S.: Uncertainty and the semantic web. Intell. Syst. IEEE **21**(5), 84–87 (2006)
43. Vail, D.L., Veloso, M.M., Lafferty, J.D.: Conditional random fields for activity recognition. In: Proceedings of the 6th international joint conference on Autonomous agents and multiagent systems, pp. 235. ACM (2007)
44. Van Kasteren, T., Noulas, A., Englebienne, G., Kröse, B.: Accurate activity recognition in a home setting. In: Proceedings of the 10th international conference on Ubiquitous computing, pp. 1–9. ACM (2008)
45. Walczak, B., Massart, D.: Rough sets theory. Chemometr. Intell. Lab. Syst. **47**(1), 1–16 (1999)

46. Wang, X., Ji, Q.: Incorporating contextual knowledge to dynamic bayesian networks for event recognition. In: Pattern Recognition (ICPR), 2012 21st International Conference on, pp. 3378–3381. IEEE (2012)
47. Welch, G., Bishop, G.: An introduction to the kalman filter (1995)
48. Yen, J.: Generalizing the dempster–shafer theory to fuzzy sets. In: Classic Works of the Dempster-Shafer Theory of Belief Functions, pp. 529–554. Springer (2008)
49. Zhang, W., Chen, F., Xu, W., Cao, Z.: Decomposition in hidden markov models for activity recognition. In: Multimedia Content Analysis and Mining, pp. 232–241. Springer (2007)