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A Sensor-Based Scheme for Activity Recognition in Smart Homes using Dempster-Shafer Theory of Evidence

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Abstract
This paper proposes a scheme for daily activity recognition in sensor-based smart homes using Dempster-Shafer theory of evidence. For this purpose, opinion owners and their belief masses are constructed from sensors and employed in a single-layered inference architecture. The belief masses are calculated using the beta probability distribution function. The frames of opinion owners are derived automatically for activities to achieve more flexibility and extensibility. Our method is verified via two experiments. In the first experiment, it is compared with a naïve Bayes approach and three ontology-based methods. In this experiment, our method outperforms the naïve Bayes classifier, having 88.9% accuracy. However, it is comparable and similar to the ontology-based schemes. Since no manual ontology definition is needed, our method is more flexible and extensible than the previous ones. In the second experiment, a larger dataset is used, and our method is compared with three approaches that are based on naïve Bayes classifiers, hidden Markov models, and hidden semi-Markov models. Three features are extracted from the sensors' data and incorporated in the benchmark methods, making nine implementations. In this experiment, our method shows an accuracy of 94.2% that, in most cases, outperforms the benchmark methods or is comparable to them.

Keywords: *Activity Recognition, Dempster-Shafer Theory of Evidence, Smart Homes.*

1. Introduction

With the rapid population ageing that is currently occurring across the world, the need for aged health care, and social and technology services will increase [1]. Studies show that elderly people would prefer to stay at home until it is impossible for them to do so, rather than move into a residential care [2], and that the benefits of home care are enormous, both to the individuals and to the state. Therefore, they must be able to do so safely at a reasonable cost. One possible solution is through the use of remote monitoring technologies, which can increase the level of security. Through automatically inferring human activities, care-givers can monitor the health and behavioral status of elderly people and provide them with essential services.

A sensor network is an efficient tool for remote monitoring. Currently, a wide range of sensors including contact sensors, accelerometers, audio and motion detectors, to name but a few, are available for activity monitoring. Based on the way the sensors are deployed, the task of senor-based activity recognition can be classified in two main categories: wearable sensor-based, and dense sensing-based activity recognition. Wearable sensors are positioned on human body and monitor features that depict the person's state such as body position and movement, while in dense sensing-based activity recognition, sensors are attached to objects, and activities are monitored by detecting user-object interactions. In this work, we focus on the dense sensing-based activity recognition.

The accuracy of an activity recognition process is affected by different levels and sources of uncertainty [3]. For instance, in [4-6], the uncertainty is considered to stem from both the sensor hardware failures and the probabilistic nature of human activities. However, uncertainty may be due to other sources such as misplacement of sensors or modeling inefficacies [3]. Sensor data fusion techniques such as Dempster-Shafer theory provide a promising solution to mitigate the effect of uncertainty, especially when the inconsistency between sensor data is not very high [7]. Fusion techniques are required to combine data from multiple sensors in order to achieve more accurate inferences since data from a single sensor does not provide sufficient evidence to infer an activity [8].

Several classification methods have been proposed for human activity recognition (HAR). They are categorized into three casts: data-driven, knowledge-driven, and hybrid methods based on their modeling schemes [9]. Among these, the Dempster-Shafer theory (DST) is known as an effective approach to deal with uncertainty and to fuse sensor data. DST can show better results in a reasoning scheme under unknown probability circumstances [10]. Approaches described in [4-6], and [11-15] are instances in which DST is incorporated for HAR. They will be discussed in more detail in the next section. However, in these approaches, static ontology definitions for activities are made available manually, and activity recognition schemes are implemented accordingly. Manual ontology definition for activities might be a complicated and error-prone task in environments with unknown human activity patterns.

In this paper, we introduce a novel method to extract the ontology definitions of activities of daily life (ADLs) automatically with the aim of using DST for HAR as a data fusion formalism. We propose a method to extract the frame of opinion owners (i.e. objects that have a degree of uncertainty, belief, and disbelief about an activity) for each activity automatically in order to accomplish this task. Opinion-owners are created from sensor nodes, and their belief masses for activities are calculated based on the beta probability distribution function, as represented in subjective logic [16,17]. The frame of opinion-owners for each activity is determined based on their uncertainty, belief, and disbelief about that activity. Having a sequence of sensor activations, a set of triggered opinion owners is calculated, and their belief masses for possible activities are fused using the Dempster's combination rule. Eventually, based on the fusion results, a decision is made about the happening activity. Two experiments are implemented to evaluate the performance of the proposed method. The proposed method is used to detect several activities within single resident environments.

The remainder of the paper is organized as what follows. In section 2, we provide an analytic survey on the literature of the subject. The Dempster-Shafer theory of evidence is introduced in section 3. Section 4 and its sub-sections address the proposed activity recognition method. A work through example is illustrated in section 5. In section 6, simulation results are shown, and finally section 7 concludes the paper.

2. Related works

There is an intense research literature on the human activity recognition. Generally speaking, they can be classified into two main categories based on their activity modeling schemes. They are *data-driven* versus *knowledge-driven* activity recognition. A third emerging category, namely *hybrid-methods* has been introduced by researchers, which uses the characteristics of both previous methods [18,19].

Data-driven activity recognition is based on learning activity models from pre-existent datasets of resident's behaviors using data mining and machine learning techniques. Probabilistic graphical models, frequent pattern mining-based approaches, and some other machine learning techniques such as the nearest neighbor classifiers (NN), decision trees, and support vector machines (SVM) are common instances of data-driven activity recognition methods.

Probabilistic graphical models provide formal mechanisms for learning activity models, and inference. These models use a template graph structure to represent the dependencies among the observed random variables (sensor readings) and the unknown variables (activity labels). Given a sequence of observations, the template graph is unrolled, and the most likely sequence of unknown variables will be estimated using a formal inference method (e.g. Viterbi algorithm) [20,21]. Various types of such graphical models exist based on the characteristics of the template graph and the unrolling rules. Naive Bayes classifiers (NBCs)[22,23], Dynamic Bayesian networks (DBNs) [24,25], hidden Markov models (HMMs) [26-28], hidden semi-Markov models (HSMMs) [28,29], coupled HMMs (CHMMs) [30,31], conditional random fields (CRFs) [26,28,32,33], skip-chain CRFs (SCCRFs) [26,34], factorial CRFs (FCRFs) [31], latent dynamic CRFs (LDCRFs) [35], and some other variants of such models are common instances that have been used for HAR. For instance, in NBCs, only the dependency of the current sensor observation with the hidden variables (activity labels) is modeled and temporal information is weakly supported; in HMMs and its variants, a directed acyclic graph (DAG) represents the temporal dependency of the current activity label (hidden variable) with the previous ones; in HSMMs, the duration of an activity (hidden state) is modeled explicitly by a duration variable; in CRFs and its variants, the unrolled graph is an undirected graph that captures the joint dependency of the activities; in SCCRF, skip chains are added to the unrolled graph based on some heuristics to model long range dependencies; and in FCRFs and CHMMs, there are more than one channel of inter-connected CRFs and HMMs, respectively, to infer concurrent activities.

Frequent pattern mining approaches show promising performances when applied to HAR. Generally, such methods try to find frequent patterns throughout the sensor data stream for further interpretation as activities. The approaches of [36-38] are instances of such works, in which the concepts of emerging patterns [36] and compression [37,38] are used to unearth the frequent patterns.

Among the other data-driven techniques, the K-nearest neighbor (KNN), decision trees, and support vector machines (SVMs) are the common approaches that have been used for HAR. In KNNs, a new sequence of observations (e.g. sensor firings) is compared with a set of training sequences, and the k most closely matching sequences vote for the activity label [39]. In [39], it is also shown that the simple KNN approach is outperformed by decision trees. In [40] (and similarly, in [41]), a support vector machine (SVM) is used to classify the features that have been computed for fixed-length time frames/windows into daily activities. In [42], a one-class SVM is hired to recognize abnormal activities. Also in [43], SVM is used to classify the sensor events based on the features calculated out of a dynamic sliding window.

In knowledge-driven activity recognition, activity models are directly acquired by exploiting a rich prior knowledge in the domain of interest using knowledge engineering and management technologies. This usually involves knowledge acquisition, formal modeling, and representation. Inference can also be done using the formal reasoning or statistical analysis. Approaches of [44] and [45] are instances in which the sensor activations in a period of time are mapped to pre-defined static activity ontologies, and then a formal logical reasoning scheme is hired to infer the associated activities. The approaches of [46] and [47] are other instances of knowledge-driven methods, in which static ontologies are hired for HAR. However, in addition to static manual ontology definition, which can be an error-prone task due to insufficient or inefficient domain specific knowledge, another criticism about these approaches is that they manage uncertainty poorly [9,46].

There are also some hybrid approaches that try to benefit from the features of both data- and knowledge-driven HAR processes by fusing them in a single modeling approach. The works of [18, 19] are instances of such methods. In [18], an ontology-based hybrid approach for activity modeling is proposed, where learning techniques are also developed to learn specific user profiles. The presented scheme is capable of learning descriptive properties of activities. In [19], an approach is proposed to use the data-driven techniques to evolve the knowledge-driven activity models with a user’s behavioral data. In these schemes, the ontologies will have a dynamic nature, although they do not consider uncertainty as a main concern.

The above-mentioned activity recognition approaches do not consider the uncertainty as a key point in their procedures. Therefore, we aim at using DST, which can mitigate the uncertainty of sensor data by its data fusion facilities. Among HAR methods, the knowledge-driven approaches of [4-6], and [11-15] are instances that deal with uncertainty. In these methods, DST is hired for inference under uncertainty as follows. However, these approaches are also based on manual ontology definitions.

In [4] and [5], the uncertainty is supposed to stem from sensor hardware errors and human activity variations. In [4], the belief masses of sensors about activities are calculated statistically and discounted by fixed rates. The sensors are mapped to activity ontologies, and then the discounted belief masses of temporally correlated triggered sensors are fused using DST to decide about the happening activity. This approach is named BDS throughout the paper, and is compared with our proposed method. In [5], a hierarchal lattice structure is proposed for activity inference. In this approach, the hierarchical lattice structure of the activity models is composed of three types of layers, namely object, context, and activity layers. The elements of each layer are connected to those of the next layer based on the ontology definition of the activity, and a weight factor is assigned to each connection, representing the uncertainty associated with their relation. Sensors are mapped to the lattice structure, and the belief masses are propagated from the first to the last layer and combined using the Dempster's combination rule. In this work, two variations of the architecture with two and three layers are implemented, which are called 2LDS and 3LDS, respectively, throughout the paper. Our proposed method is also compared with 2LDS and 3LDS in the experiments. In [6], the approach of [5] is improved by introducing a new weight factor method for the lattice-based evidential fusion. The approach of [14] is similar to that of [6], in that they are both based on layered lattice structures of activities that have been introduced in [5]. The difference is that in [14], an alternative weighting scheme is introduced, and the results are comparable to those provided in [5] and [6]. In [12], an approach similar to that of [5] is implemented. In this work, it is shown that by incorporating the Dempster's combination rule, the more the evidences are available, the more confident decisions can be made.

In [11], the activity model is represented using situation directed acyclic graphs (DAGs), which include temporal information as well. In this structure, the nodes in DAG are labeled with sensor IDs, context values, and activities. They are inter-connected in a layered style, and a weight factor is dedicated to each connection, representing the uncertainty of the relation. The activity duration and the absolute time (e.g. morning, afternoon) at which the activity usually takes place are also accommodated into DAG. To infer an activity, evidences are accumulated along the duration time of the activities, and their belief masses are fused using the Dempster's combination rule.

In [13], the Dempster-Shafer rules are changed to include temporal information in belief mass assignment and combination to recognize activities. However, this work makes use of contexts of activities in the form of directed acyclic graph as a prior knowledge. In [14], a mapping technique for converting the raw sensors' data into a high-level activity knowledge is proposed, and a conflict resolution technique for the Dempster-Shafer theory is introduced to optimize decision-making. This work hires prior knowledge of activities in the form of directed acyclic graphs for belief propagation as well.

As it can be seen, knowledge-driven methods that incorporate DST hire a static structure for each activity based on the activity ontology, map the installed sensors into that structure, and then use a fusion technique, i.e. the Dempster's combination rule, to fuse the beliefs of pre-determined activity evidences, and decide about the happening activity. A criticism about these procedures is the generality of the ontology definitions and the complexities of deriving them, especially in situations with unknown activity patterns. Thus we propose a method to derive the evidences of activities in an automatic way, i.e. not based on predefined ontologies, fuse their beliefs via DST, and decide about the happening activity.

3. Dempster-Shafer theory of evidence

The Dempster-Shafer theory (DST) is a mathematical theory of evidence [10]. DST can combine evidences from different sources and arrive at a degree of belief (represented by a belief function) that takes into account all available evidences.

In DST, a frame of discernment, called Θ, is a domain of all possible elements of interest. Each proposition pertains to a subset of Θ. A piece of evidence that supports one or more propositions can be expressed by a basic probability assignment (BPA) function $m: 2^{\Theta} \rightarrow [0,1]$ such that $m(\emptyset) = 0$ and $\sum_{A \subseteq \Theta} m(A) = 1$, where $\emptyset$ is the empty set. The belief function can be expressed as follows:

$$Bel(X) = \sum_{A \subseteq X, X \subseteq \Theta} m(A) \tag{1}$$

where, $Bel(X)$ represents the total degree of support for proposition X. Two BPAs, namely m_1 and m_2, from two sources of evidence can be combined using the Dempster's combination rule as:

$$m_1 \oplus m_2 = \begin{cases} \dfrac{1}{1-K} \sum\limits_{A_i \cap A_j}^{i,j} m_1(A_i) m_2(A_j) \; if \;\; A \neq 0 \\ 0 \;\; if \;\;\; A = 0 \end{cases} \tag{2}$$

where, K is the inconsistency factor, which can be calculated as follows:

$$K = \sum\nolimits_{A_i \cap A_j = \phi}^{i,j} m_1(A_i) m_2(A_j). \tag{3}$$

The more K is closer to 1, the more the evidences are conflicting. Equation (2) can also be used to combine more than two pieces of evidence, as in (4). The obtained result represents the effect of all pieces of evidence.

$$m_1 \oplus \cdots \oplus m_n = ((m_1 \oplus m_2) \oplus \cdots \oplus m_n). \tag{4}$$

4. Proposed activity inference structure

The proposed method has two phases, namely the training phase and the inference phase. In the training phase, two tasks are accomplished using the training set: 1- opinion-owners are made out of sensors and their BPAs are calculated, as described in sub-section 4.1, 2- based on BPAs, the frame of opinion-owners for each activity is extracted automatically, as explained in sub-section 4.2. In the inference phase, two tasks are carried out as well: 1- having a sequence of triggered sensors, temporally-correlated sensors are extracted, as presented in sub-section 4.3, 2- the corresponding activity for each sequence of temporally-correlated sensors is inferred, as described in sub-section 4.4.

In this work, we used the binary switch sensors. Whenever an activity happens, different sensors would be triggered from the start to the end of the activity. The sensors record and send their data to a base station for further processing. Their data is simply their IDs along with their activation and deactivation times.

4.1. Opinion owners and their BPAs

Opinion-owners are the evidences that have a degree of uncertainty, belief, and disbelief about an activity. In the case of sensor-based smart homes, since the resident triggers a specific pattern of consecutive sensors for each activity, the sequences of sensors can testify about the activities. Therefore, ordered n-tuples ($n = 1, \dots, d$) of sensors are considered as opinion-owners, and are shown within $< \cdots >$ signs, i.e. an n-tuple is composed of n triggered sensors from the input sensor stream, ordered by their occurrence time. The sensor triggers are due to the resident's activities. Given an input sensor stream, all n-tuples with lengths $n = 1, \dots, d$ are extracted as opinion-owners, where $d \in \mathbb{N}$ is a constant that is determined as a system design parameter. The belief, disbelief, and uncertainty of opinion-owners can be calculated by beta distribution, as illustrated in [16]. These calculations are taken in the following for more clarification (i.e. Equations (5)-(11)).

The posterior probabilities of binary events can be represented by the beta distribution [16]. The beta-family of density functions is a continuous family of functions indexed by the two parameters α and β. The beta distribution can be expressed using the gamma function, as follows:

$$\begin{cases} f(p \mid \alpha, \beta) = \dfrac{\Gamma(\alpha+\beta)}{\Gamma(\alpha)\Gamma(\beta)} p^{\alpha-1}(1-p)^{\beta-1} \\ \Gamma(t) = \displaystyle\int_0^{\infty} x^{t-1} e^{-x} dx \end{cases} \tag{5}$$

where, $\Gamma(.)$ is the gamma function, $0 \le p \le 1$, and $\alpha, \beta \ge 0$, with the restriction that probability value $p \ne 0$ if $\alpha < 1$ and $p \ne 1$ if $\beta < 1$. The expectation value of the beta distribution is given by:

$$E(p) = \frac{\alpha}{\beta+\alpha}. \tag{6}$$

For a binary event space, namely $\{x, \sim x\}$, let r and s denote the number of positive and negative past observations that support x and $\sim x$, respectively. Let p denote the probability of x and f be a probability density function over the probability variable p. Having a prior uniform distribution over $\{x, \sim x\}$, f is characterized by r and s, as follows in (7) [16].

$$f(p \mid r, s) = \frac{(r+s+2)}{(r+1)(s+1)} p^r (1-p)^s. \tag{7}$$

Equation (7) is a beta distribution with $\alpha = r + 1$ and $\beta = s + 1$. Therefore, the expectation of p, named $E(p)$, can be obtained by substituting α and β in (6), as follows:

$$E(p) = \frac{r+1}{r+s+2}. \tag{8}$$

For a binary event space, namely $\{x, \sim x\}$, let b, d, and u represent the belief, disbelief, and uncertainty about proposition x such that $b + d + u = 1$. The expectation of probability of x, named E_x, can also be obtained by (9) [16], [17].

$$E_x = b + \frac{1}{2}u. \tag{9}$$

The values for b, d, and u are derived by applying an equality between (8) and (9), i.e. E_x and $E(p)$, with the restriction that $b + d + u = 1$, as:

$$\begin{cases} E_x = E(p) \\ b+d+u=1 \end{cases} \Rightarrow \begin{cases} b + \dfrac{1}{2}u = \dfrac{r+1}{r+s+2}. \\ b+d+u=1 \end{cases} \tag{10}$$

The solution of (10) is required to make b an increasing function of r, and d an increasing function of s, so that there is an affinity between b and r, and between d and s [16]. Also u is required to be a decreasing function of r and s [16]. By applying this affinity requirement, the solution of (10) will be:

$$\begin{cases} b = \dfrac{r}{r+s+2} \\ d = \dfrac{s}{r+s+2}. \\ u = \dfrac{2}{r+s+2} \end{cases} \tag{11}$$

Regarding the DST notations from the previous section, let $m_O(E)$ denote the BPA of opinion owner O about event $E \subseteq \{x, \sim x\}$ for a binary event space $\{x, \sim x\}$. Sub-set $E = \{x\}$ denotes "event x is happening", $E = \{\sim x\}$ denotes "event x is not happening", $E = \{x, \sim x\}$ stands for "we are uncertain on whether x or $\sim x$ is happening", and $E = \phi$ is considered as an impossible event, i.e. $m_O(\phi) = 0$. Furthermore, let r_x^o and s_x^o denote the number of past positive and negative observations of O that support x and $\sim x$, respectively. If b_x^o, d_x^o, and u_x^o represent the belief, disbelief, and uncertainty of opinion-owner O about happening of x, then the BPAs of O are defined by substituting r and s in (11) for r_x^o and s_x^o, as follows:

$$\begin{cases} m_O(\{x\}) = b_x^o = \dfrac{r_x^o}{r_x^o + s_x^o + 2} \\ m_O(\{\sim x\}) = d_x^o = \dfrac{s_x^o}{r_x^o + s_x^o + 2} \\ m_O(\{x, \sim x\}) = u_x^o = \dfrac{2}{r_x^o + s_x^o + 2} \end{cases} . \qquad (12)$$

It is clear that the equations in (12) are derived by substituting positive and negative observations (r_x^o and s_x^o) in the equations in (11), respectively. In the case of HAR, the frame of discernment for an activity, namely a, will be $\{a, \sim a\}$, where a represents the occurrence of the activity and $\sim a$ represents that the activity is not taking place. Consider $m_O(A)$ as the belief mass of opinion-owner $O = < s_1, s_2, \dots, s_n >$ for event $A \subseteq \{a, \sim a\}$. Also let $N(O\,,\, a)$ represent the number of times that the n-tuple of opinion-owner $O = < s_1, s_2, \dots, s_n >$ has been a subsequence of the ordered triggered sensors for activity a in the training set. If the happening of a is considered as a positive and $\sim a$ as a negative observation, then the numbers of positive and negative observations of opinion-owner O for activity a are considered as $r_a^O = N(O\,,\, a)$ and $s_a^O = N(O\,,\, \sim a)$, respectively. Thus the BPAs of opinion-owner O for activity a will be obtained directly by substituting r_x^O, s_x^O, and x in (12) for r_a^O, s_a^O, and a, respectively. The result obtained is shown in (13).

$$\begin{cases} m_O(\{a\}) = b_a^O = \dfrac{N(O\,,a)}{N(O\,,a) + N(O\,,\sim a) + 2} \\ m_O(\{\sim a\}) = d_a^O = \dfrac{N(O\,,\sim a)}{N(O\,,a) + N(O\,,\sim a) + 2} \\ m_O(\{a, \sim a\}) = u_a^O = \dfrac{2}{N(O\,,a) + N(O\,,\sim a) + 2} \end{cases} . \qquad (13)$$

4.2. Frame of opinion-owners

Let S denote an opinion-owner and a denote an activity label. With the notations of (12) and (13), an opinion about activity a can be represented by a triple (b_a^S, d_a^S, u_a^S). Since $b_a^S + d_a^S + u_a^S = 1$, the domain of all opinions for a can be shown by the equilateral triangle of figure 1. This triangle is introduced as opinion triangle or opinion space in [17]. Axes u, b, and d correspond to uncertainty, belief, and disbelief, respectively. These axes run from one edge to the opposite vertex. Coordination of a point can be calculated by drawing perpendicular lines from the point to the corresponding axes and calculating the distance of the intersection point from the origin.

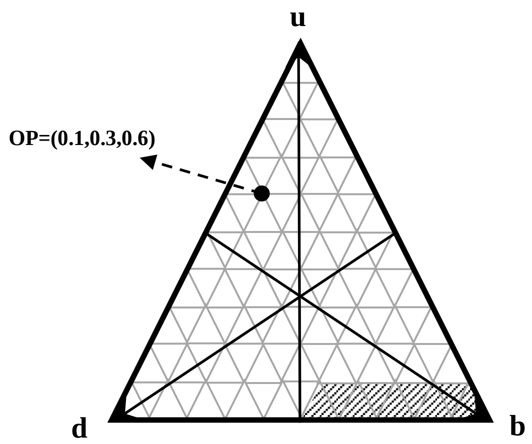

Figure. 1. Opinion triangle for an activity, namely a. Point OP shows an opinion with $b_a^S = 0.1, d_a^S = 0.3$, and $u_a^S = 0.6$, where S is an opinion-owner. The dashed area shows an accept area for activity a [17].

The frame of opinion-owners for an activity is comprised of the opinion-owners that have been triggered frequently whenever the activity has taken place. Therefore, the beliefs of these opinion-owners for that activity should be high, and their disbeliefs and uncertainties for that activity should be low. Therefore, the frame of opinion-owners for activity a will include the opinion-owners whose opinions about a fall within an area of the opinion triangle with a high belief, low disbelief, and low uncertainty level. This area is named accept area in our approach. The dashed area in figure 1 shows an accept area for activity a with uncertainty degrees less than or equal to 0.1, beliefs of more than or equal to 0.5, and disbeliefs of less than or equal to 0.5. Each activity would have its specific accept area. The accept area is one of the input parameters of our scheme.

4.3. Temporal correlation in a sequence of sensors

Let $S = s_1, s_2, \ldots, s_n$ represent a sequence of n sensor triggers that corresponds to a number of activities in a period of time. Suppose that we want to infer the activities associated with S. A prerequisite task for inference is to find the subsequences of S that have been triggered for an identical activity, although the activity is not known yet. To extract such subsequences, the temporal correlation of sensors' activations is considered, i.e. sensors with close activation times are possibly triggered due to the same activity. We name such sensors temporally correlated. Therefore, to decide which sensors are temporally correlated, a clustering algorithm can be used. To do this, the k-means clustering algorithm is used to cluster the sensors based on their activation times. After clustering, the sensors in each cluster are considered as temporally correlated and an activity is inferred for each cluster. Note that in k-means, the number of clusters must be known beforehand. In this case, since we do not know the number of clusters, we assume the maximum number of possible clusters, and finally, ignore the clusters with no instance. The maximum number of clusters will be equal to the number of sensors in S, i.e. n, because in the worst case, every single sensor would be in a separate cluster.

As an example, consider a part of data in one day of sensor activations from a dataset by VanKasteren et al. [28], as shown in table 1. We want to infer the activities for this day. In the first step, the sensors are clustered. The sequences of sensors for each cluster are shown in table 2. Table 2 is called relation matrix throughout the paper. In the second step, activities will be inferred for the sequences of sensors in each row of the relation matrix. Sensors in each row are in the ascending activation time order. After inferring an activity for each row, the time interval from the activation of the first sensor to the last one in the row will be labeled with the inferred activity. If a real world activity is inferred correctly within its real time interval, a true positive, and otherwise, a false negative will be recorded for it. A complete activity inference example is illustrated in section 5.

Table 1. Sensor activations for a single day.

Activation Time	Sensor ID	Activation Time	Sensor ID
3/7/2008 6:59	24	3/7/2008 8:49	7
3/7/2008 6:59	24	3/7/2008 8:49	8
3/7/2008 6:59	6	3/7/2008 8:50	9
3/7/2008 7:00	6	3/7/2008 8:50	23
3/7/2008 8:38	24	3/7/2008 8:50	8
3/7/2008 8:38	24	3/7/2008 8:51	8
3/7/2008 8:44	6	3/7/2008 9:07	5
3/7/2008 8:45	14	3/7/2008 9:15	5
3/7/2008 8:45	8	3/7/2008 9:29	12
3/7/2008 8:49	8	3/7/2008 9:29	12

Table 2. Relation matrix for a single day.

	Sensor1	Sensor2	Sensor3	Sensor4
cluster1	24	24	6	6
cluster2	24	24	----	----
cluster3	6	14	8	----
cluster4	8	7	8	----
cluster5	9	23	8	8
cluster6	5	----	----	----
cluster7	5	----	----	----
cluster8	12	12	----	----

4.4. Inference Architecture

After the training phase, to infer the activities for a sequence of triggered sensors, firstly, the temporally correlated sensors are extracted, as illustrated in the previous sub-section (sub-section 4.3). Then, for each sequence of temporally correlated sensors, a single activity is inferred. Let $S = s_1, s_2, s_3, \ldots, s_l$ represent a temporally correlated sequence of sensors in the ascending activation time order, for which a single activity should be inferred. The proposed architecture of figure 2 is used to infer the activity that corresponds to S. In this architecture, at first, all triggered opinion-owners, i.e. n-tuples with $n =$

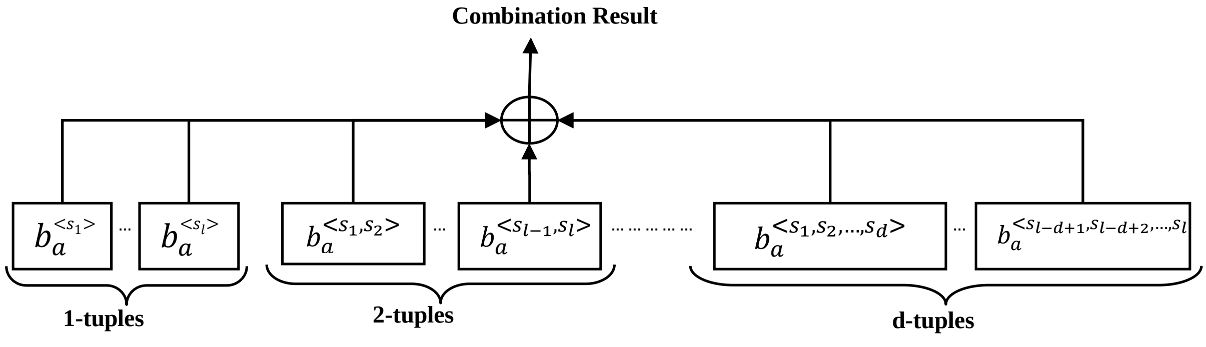

Figure 2. Belief mass combination for activity a. Belief masses of triggered opinion-owners that belong to a's frame of opinion-owners are combined using Dempster's combination rule.

$1,2,3,\dots,d$ are extracted from S. Parameter d determines the number of n-tuple categories in the architecture. For example, for $S' = s_1, s_2, s_3$ and $d = 3$, three 1-tuples ($< s_1 >, < s_2 >, < s_3 >$), three 2-tuples ($< s_1, s_2 >, < s_1, s_3 >, < s_1, s_2 >$), and one 3-tuple ($< s_1, s_2, s_3 >$) can be extracted as opinion-owners. Note that in S', $< s_2, s_1 >$ is not considered as a triggered opinion-owner because sensor s_1 is activated before s_2 in S. This temporal order can take the activation time order into consideration. For example, suppose that a switch sensor, namely s_1, is installed for the bedroom lamp, and is triggered whenever the lamp turns on or off, and switch sensor s_2 is installed for the bedroom door, and is triggered whenever the door is opened. Consider that someone opens the door and then turns on the lights whenever enters the bedroom, and vice versa when exiting. Thus, the sequence $< s_2, s_1 >$ shows an entrance activity, while the sequence $< s_1, s_2 >$ shows an exit activity. In fact, different sensor activation orders are evidences for different actions. Thus, different sensor orders are considered as different opinion-owners.

After the first step, for each individual activity, namely a, the belief masses of the triggered opinion-owners that belong to a's frame of opinion-owners are fused via the Dempster's combination rule, as shown in figure 2. Finally, the activity with the maximum combined belief result is considered as the corresponding one.

5. Work through example

In this section, the inference scheme is illustrated through an example. The training dataset used in the following sub-sections consists of the sensors' activation data and annotated activities of table 3 and table 4, respectively.

Table 3. Sensor data.

Activation Time	Sensor ID	Activation Time	Sensor ID
3/6/2008 4:38:06	6	3/6/2008 9:04:51	6
3/6/2008 4:38:30	8	3/6/2008 9:04:54	8
3/6/2008 4:38:48	14	3/6/2008 9:38:53	6
3/6/2008 8:39:37	6	3/6/2008 9:40:02	14
3/6/2008 8:40:11	14	3/6/2008 9:42:31	6
3/6/2008 9:04:35	8		

Table 4. Activity annotations.

Index	Start Time	End Time	Activity
1	3/6/2008 4:38:02	3/6/2008 4:38:56	Use Toilet
2	3/6/2008 8:39:35	3/6/2008 8:40:18	Use Toilet
3	3/6/2008 9:04:05	3/6/2008 9:09:56	Prepare Breakfast
4	3/6/2008 9:38:48	3/6/2008 9:43:12	Use Toilet

There are three sensors, i.e. 6, 8, and 14, and two activities, i.e. "Use Toilet" and "Prepare Breakfast", in the dataset. It is supposed that one activity can take place at any time. The training and inference phases are exemplified in the following sub-sections.

5.1. Training

In the training phase, the first step is to make the set of opinion-owners and calculate their BPAs. As already illustrated, opinion-owners are the set of n-tuples with $n = 1,2,\dots,d$, that are made out of sensors. We consider $d = 2$ and obtain the set of all 1-tuples and 2-tuples from sensor IDs. It can be seen that there are 3 sensors in the training set. Thus there will be 9 opinion-owners, as shown in the first column of table 6.

To calculate the BPAs of opinion-owners for activities, the sequence of sensors that are triggered for each annotated activity is obtained, and then (13) is applied. A sensor with an activation time greater than the start and less than the end time of an activity belongs to that activity's sequence of triggered sensors. The start and end of an activity are annotated in table 4, which shows the triggered sensors for each activity of the training set.

Now let's calculate the BPAs of the opinion-owner $< 6 >$ for "Use Toilet" activity. In order to incorporate (13), the number of times where the activity "Use Toilet" has happened along with the opinion-owner $< 6 >$, i.e. $N(6, \text{"}Use\ Toilet\text{"})$, and the number of times where the activity "Use Toilet" has not happened along with opinion-owner $< 6 >$, i.e. $N(6, \sim\text{"}Use\ Toilet\text{"})$ must be calculated. As it can be seen in table 5, opinion-owner $< 6 >$ has been triggered in three "Use Toilet" activities and also in one "Prepare Breakfast" activity (repeated triggers for the same activity are counted once). Thus $N(< 6 >, \text{"}Use\ Toilet\text{"}) = 3$ and $N(6, \sim\text{"}Use\ Toilet\text{"}) = 1$. Therefore, by applying (13) for "Use Toilet" activity, we will have (14) as in the following:

$$\begin{cases} m_{\langle 6\rangle}\left(\{\text{"Use Toilet"}\}\right) = \\ \dfrac{N\left(\langle 6\rangle, \text{"Use Toilet"}\right)}{N\left(\langle 6\rangle, \text{"Use Toilet"}\right) + N\left(\langle 6\rangle, \sim\text{"Use Toilet"}\right) + 2} = \dfrac{3}{6}, \\ m_{\langle 6\rangle}\left(\{\sim\text{"Use Toilet"}\}\right) = \\ \dfrac{N\left(\langle 6\rangle, \sim\text{"Use Toilet"}\right)}{N\left(\langle 6\rangle, \text{"Use Toilet"}\right) + N\left(\langle 6\rangle, \sim\text{"Use Toilet"}\right) + 2} = \dfrac{1}{6}, \\ m_{\langle 6\rangle}\left(\{\text{"Use Toilet"}, \sim\text{"Use Toilet"}\}\right) = \\ \dfrac{2}{N\left(\langle 6\rangle, \text{"Use Toilet"}\right) + N\left(\langle 6\rangle, \sim\text{"Use Toilet"}\right) + 2} = \dfrac{2}{6}. \end{cases} \quad (14)$$

As another instance, let's calculate BPAs of opinion-owner $< 6{,}14 >$ for "Use Toilet" activity. This opinion-owner has been triggered in 3 "Use Toilet" activities, i.e. the opinion-owner $< 6{,}14 >$ is a subsequence of three sensor sequences of "Use Toilet" activities in table 5 (note that in the first "Use Toilet" activity in table 5, sensors 6 and 14 are not consecutive but their activation order is preserved). We can see that $< 6{,}14 >$ has not been triggered for "Prepare Breakfast". Therefore, $N(< 6{,}14 >, \text{"}Use\ Toilet\text{"}) = 3$, and $N(< 6{,}14 >, \sim\text{"}Use\ Toilet\text{"}) = 0$. By applying (13), we will have (15) as in the following.

$$\begin{cases} m_{\langle 6,14\rangle}(\{\text{"Use Toilet"}\}) = \\ \dfrac{N(\langle 6,14\rangle, \text{"}UseToilet\text{"})}{N(\langle 6,14\rangle, \text{"}UseToilet\text{"}) + N(\langle 6,14\rangle, \sim \text{"}UseToilet\text{"}) + 2} = \dfrac{3}{5}, \\ \\ m_{\langle 6,14\rangle}(\{\sim \text{"Use Toilet"}\}) = \\ \dfrac{N(\langle 6,14\rangle, \sim \text{"}UseToilet\text{"})}{N(\langle 6,14\rangle, \text{"}UseToilet\text{"}) + N(\langle 6,14\rangle, \sim \text{"}UseToilet\text{"}) + 2} = 0, \\ \\ m_{\langle 6,14\rangle}(\{\text{"}UseToilet\text{"}, \sim \text{"}UseToilet\text{"}\}) = \\ \dfrac{2}{N(\langle 6,14\rangle, \text{"}UseToilet\text{"}) + N(\langle 6,14\rangle, \sim \text{"}UseToilet\text{"}) + 2} = \dfrac{2}{5}. \end{cases} \tag{15}$$

The process will be the same for the other opinion-owners and activities. All the opinion-owners and their BPAs for "Use Toilet" and "Prepare Breakfast" are depicted in table 6.

Table 6. Opinion owners and their BPAs for activities.

	"Use Toilet" Activity			"Prepare Breakfast" Activity		
OW	**B**	**D**	**U**	**B**	**D**	**U**
<6>	0.5	0.17	0.33	0.17	0.5	0.33
<8>	0.25	0.25	0.5	0.25	0.25	0.5
<14>	0.6	0	0.4	0	0.6	o.4
<6,8>	0.25	0.25	0.5	0.25	0.25	0.5
<6,14>	0.6	0	0.4	0	0.6	0.4
<8,6>	0	0.33	0.67	0.33	0	0.67
<8,14>	0.33	0	0.67	0	0.33	0.67
<14,6>	0.33	0	0.67	0	0.33	0.67
<14,8>	0	0	1	0	0	1

OW= opinion owner, B= belief, D= disbelief, U= uncertainty.

In the second step, the frame of opinion-owners for each activity should be calculated. To do this, an accept area must be defined for the activities. The opinion-owners whose opinions for an activity fall within the accept area of that activity are added to the activity's frame of opinion-owners. In this example, let's define the same area for all the activities with an uncertainty less than or equal to 0.5 and a belief greater than 0. Thus for "USE Toilet", the set of opinion owners will be $\{< 6 >, < 8 >, < 14 >, < 6{,}8 >, < 6{,}14 >\}$.

Table 5. Sequence of sensors in ascending activation time order for each activity.

Index	Activity	Sequence of sensors
1	Use Toilet	6, 8, 14
2	Use Toilet	6, 14
3	Prepare Breakfast	8, 6, 8
4	Use Toilet	6, 14, 6

Similarly, it will be $\{< 6 >, < 8 >, < 6{,}8 >\}$ for "Prepare Breakfast" activity.

In this example, we used a simple and relatively large accept area for the sake of simplicity and expressiveness. But indeed, the opinion-owners of an activity must have a low uncertainty and high belief (low disbelief) about the activity. Therefore, in practice, a more confined accept area with such characteristics must be defined to get more reliable results.

5.2. Inference

Consider the sequence of sensor activations of table 1. The first step to infer the activities for this sequence is to find the temporal correlation of sensors and obtain the relation matrix. The temporal correlation of these sensors has already been calculated in table 2.

In the second step, an activity is inferred for each cluster, i.e. each row of the relation matrix. To do this, the triggered opinion-owners for each row are extracted. Then the belief masses of the triggered opinion-owners that belong to an activity's frame of opinion-owners are combined for it using the Dempster's combination rule. The activity with the maximum combination result is inferred for the row.

Let's infer the activity pertaining to cluster 3, i.e. the sequence $S = 6{,}14{,}8$ in table 2. With $d = 2$, as determined in the training phase, the triggered opinion-owners for S will be $\{< 6 >, < 14 >, < 8 >, < 6{,}14 >, < 6{,}8 >, < 14{,}8 >\}$. Note that the triggered opinion-owners are ordered n-tuples whose sensors appear in S with the same order. For example, opinion-owners <8,6> or <14,6> have not been triggered because sensors 8 or 14 had not been triggered before 6 in S.

Next, the belief masses of the triggered opinion-owners that belong to the frame of "Use Toilet" and "Prepare Breakfast" will be combined for their corresponding activity. We can see that all opinion-owners in the frame of "Use Toilet" and "Prepare Breakfast" activities are triggered in S. The combination results are shown in (16) and (17).

$$m_{\langle 6\rangle}(\text{"Use Toilet"}) \oplus m_{\langle 8\rangle}(\text{"Use Toilet"}) \oplus m_{\langle 14\rangle}(\text{"Use Toilet"}) \oplus m_{\langle 6,8\rangle}(\text{"Use Toilet"}) \oplus m_{\langle 6,14\rangle}(\text{"Use Toilet"}) = 0.91. \quad (16)$$

$$m_{\langle 6\rangle}(\text{"Prepare Breakfast"}) \oplus m_{<8>}(\text{"Prepare Breakfast"}) \oplus m_{\langle 6,8\rangle}(\text{"Prepare Breakfast"}) = 0.30. \quad (17)$$

As it can be seen, the combination results for "Use Toilet" and "Prepare Breakfast" are 0.91 and 0.30, respectively. Thus "Use Toilet" is the inferred activity for the sequence S.

6. Simulations and results

We run two experiments to evaluate the performance of the proposed method. In the first experiment, a comparison between the proposed method and three knowledge-driven approaches, i.e. BDS, 2LDS, and 3LDS is provided. Also a comparison with a naïve Bayes method is made available. In this experiment, an activity of daily life (ADL) dataset from MIT lab [22] is used.

In the second experiment, we compare the proposed method with three data-driven activity recognition approaches. These approaches are based on NBCs, HMMs, and HSMMs, as implemented in [28]. In the second experiment, a larger dataset consisting of several frequent daily activities is used.

In both experiments, the input parameter d (that determines categories of n-tuples with $n = 1, \dots, d$) is considered to be 2, and the accept area is considered as a region in the opinion space with an uncertainty less than 0.1, a belief greater than 0.5 and a disbelief less than 0.5 for all activities.

6.1 Experiment 1

In this experiment, the proposed method is compared with the naïve Bayes activity recognition method of [22], and the approaches of BDS [4], 2LDS [5], and 3LDS [5]. An ADL dataset from MIT lab [22] is used to verify the proposed method. Subject one from the dataset is used for this simulation. In this case, 77 switch sensors are installed in a single-person apartment to collect data about the resident's activities. The sensors are installed on different appliances such as drawers, cabinets, and taps to collect resident's data. More details on the topology and data acquisition scheme are illustrated in [22].

The dataset includes two weeks of daily activities, in which a single person has done his/her daily activities. Leave-one-out cross-validation strategy, i.e. 13 days activity information for training and 1 day information for testing, is used to measure the performance of the proposed method. In this experiment, we compare our method with the others for detecting the toileting activities because this activity is the most frequent one in the dataset that happens several times a day and adequate numbers of sensors are triggered for it. Thus the training data will be sufficient. Also the ontologies based on the sensors in the state of the art approaches can be well-defined. The three ontology-based approaches, i.e. BDS, 2LDS, and 3LDS, have incorporated this activity to verify their methods, and reported their results for it as well [5].

Table 7. Results of Proposed Method for Activity Recognition.

Date	TP	FP	FN	TN	PR	RC
27/3/2003	1	1	1	12	50%	50%
28/3/2003	3	0	1	11	100%	75%
29/3/2003	5	1	3	11	83.3%	62.5%
30/3/2003	4	1	2	7	80%	66.67%
31/3/2003	2	0	1	9	100%	66.67%
1/4/2003	5	0	0	9	100%	100%
2/4/2003	3	0	2	17	100%	60%
3/4/2003	2	1	1	12	66.67%	66.67%
4/4/2003	4	1	0	13	80%	100%
5/4/2003	5	0	0	8	100%	100%
6/4/2003	7	0	2	11	100%	77.78%
7/4/2003	5	0	2	8	100%	71.42%
8/4/2003	5	1	0	7	83.3%	100%
9/4/2003	7	1	0	10	87.5%	100%
10/4/2003	6	3	1	16	66.67%	85.7%
11/4/2003	4	3	1	12	57.1%	80%
Total	**68**	**13**	**17**	**173**	**84%**	**80%**

TP= true positive, FP= false positive, FN= false negative, TN= true negative, PR= precision, RC= recall.

Table 8. Comparison of BDS, 2LDS, 3LDS, and the proposed method.

Method	PR	RC	FM	ACC
BDS	69.4%	88.3%	77.7%	81.4%
2LDS	84.7%	93.5%	88.9%	92.34%
3LDS	88.2%	80%	84.2%	86.6%
proposed method	84%	80%	82%	88.9%

PR= precision, RC= recall, FM= F-measure, ACC= accuracy.

Table 7 shows the simulation results for our method. The naïve Bayes method has provided 61.2% precision and 83.5% recall, as reported in [22]. It can be seen that the proposed method has a precision of 84%, and outperforms the naïve Bayes approach. The recall resulted from our scheme is comparable, and approximately similar to the 83.5% recall from the naïve Bayes algorithm. However, the 82% F-measure of our method is also better than that of naïve Bayes algorithm.

Table 8 provides a comparison between our algorithm and those of BDS, 2LDS, and 3LDS, as reported in [5]. It can be seen that our method is better than BDS in terms of classification accuracy, precision, and F-measure. Also it can be seen that our method is slightly different from 3LDS, having the same recall and a little difference in precision, F-measure, and accuracy. In comparison with 2LDS, the proposed method, BDS, and 3LDS have worse recall and F-measure, although the precision of the proposed method is the same as 2LDS, and its accuracy is similar to 2LDS. It can be seen that the proposed method is comparable to 2LDS and 3LDS, and is slightly different from them.

Table 9. T-test comparison of the proposed method with 2LDS, and 3LDS.

	Proposed method	Comparison with 2LDS	Comparison with 3LDS
mean	0.890	0.896	0.854
variance	0.0048	0.0151	0.0186
observations	16	16	16
pearson correlation		0.2371	0.2278
hypothesized mean difference		0	0
df		15	15
t-Stat		-0.1908	1.0371
P(T<=t) one-tail		0.4256	0.1580
t-critical one-tail		1.7530	1.7530
P(T<=t) two-tail		0.8512	0.3161
t-critical two-tail		2.1314	2.1314

A statistical analysis, i.e. paired t-test, is also performed to show that there is no significant difference between our method, 2LDS, and 3LDS. To do this, the accuracies of activity recognition schemes are calculated for each day. The average accuracy of the proposed method, 2LDS, and 3LDS were 89, 89.6, and 85.4 percent, respectively, and it seemed that they had no significant difference. To prove this, the paired t-test was carried out to compare the accuracy means at a significance level of $\alpha = 0.05$, and the null hypothesis was considered as equal accuracy means. As the results are shown in table 9, since the absolute of t-values (t-Stat) is less than the t-critical values, we fail to reject the null hypothesis, i.e. equal means. Thus the t-test testifies that there is no significant difference between the accuracies of the proposed method and those of 2LDS and 3LDS.

The main difference between 2LDS, 3LDS, and our method is the way through which the ontology definitions for the activities are derived. In the proposed method, this task is done in an automatic manner, while it is done manually in 2LDS and 3LDS. Therefore, our method is more extensible and flexible than the previous ones. It also preserves the previous method classification criteria, as the statistical analysis showed.

6.2 Experiment 2

In this experiment, the proposed method is compared to three benchmark activity recognition schemes, which are based on NBC, HMM, and HSMM classifiers, as implemented in [28] using a larger dataset than that of experiment 1. An ADL dataset by VanKasteren et. al. [28] is used for this experiment. The dataset consists of several weeks of data recorded in a real world setting. The wireless network nodes are equipped with various kinds of sensors that give binary outputs. A “0” indicates that the sensor is not in use, and a “1” indicates that the sensor is fired. The House A from dataset is selected for this experiment. In this case, 14 state change digital sensors are installed indoors, kitchen appliances, etc. Annotations are carried out by the resident using a headset and a voice-recognition software over 25 days. More details on the datasets can be found in [28].

We compared our method with the others to recognize several frequent daily activities from the dataset that happen in different places of the house consisting of “leave the house”, “use toilet”, “go to bed”, and “prepare breakfast”. Sufficient numbers of sensors are triggered for these activities, and a convenient training set will be available.

As it is stated in [28], 3 features can be extracted from sensor activations/deactivations, and employed in the three above-mentioned activity recognition processes, i.e. raw data, change-point data, and last-fired data. The definitions of these features are as follow. For more details on the features and the way they are incorporated in the benchmark methods, the reader is referred to [28].

Raw: The raw sensor representation uses the sensor data directly as it was received from the sensors. It gives a 1 when the sensor is firing and a 0 otherwise.

Change-point: The change point representation indicates when a sensor event takes place. More formally, it gives a 1 when a sensor changes state (i.e. goes from zero to one or vice versa) and a 0 otherwise.

Last-fired: The last-fired sensor representation indicates which sensor fired last. The sensor that changed state last, continues to give 1 and changes to 0 when another sensor changes state.

We incorporated these features in the benchmark methods, as demonstrated in [28]. The classification criteria were calculated using the leave-one-out cross-validation strategy for each activity, and then averaged for each method.

The results of experiment 2 are presented in table 10. It can be seen that the proposed method outperforms all of the three methods that use raw data in terms of precision, recall, f-measure, and accuracy. Also our method outperforms the naïve Bayes approach that uses change-point feature. It can be seen that the proposed method is slightly different from the other approaches, and in most of the cases, it has a better performance.

Table 10. The results of experiment 2.

Method	Feature	PR	RC	FM	ACC
naïve Bayes	raw data	74.4%	58.4%	64.9%	77.6%
	change-point	73.5%	53.3%	61.3%	56.3%
	last-Fired	86.8%	74.6%	80.0%	95.9%
HMM	raw data	56.7%	66.3%	60.0%	61.0%
	change-point	81.5%	84.2%	82.6%	90.1%
	last-Fired	76.4%	84.0%	79.6%	93.0%
HSMM	raw data	57.3%	67.7%	60.8%	62.0%
	change-point	82.1%	84.9%	83.2%	91.5%
	last-Fired	81.1%	86.8%	83.5%	95.0%
proposed method	-----	86.7%	84.4%	85.5%	94.2%

PR= precision, RC= recall, FM= F-measure, ACC= accuracy.

7. Conclusion and future work

In this paper, a single layered architecture for human activity inference within smart homes was proposed. In this work, n-tuples (with $n = 1,2,3,\ldots,d$) of sensor IDs formed the set of opinion-owners. The belief masses were calculated using Beta probability distribution function through the training data. Having a sequence of triggered switch sensors, the Dempster's combination rule was employed to combine the belief masses of triggered opinion-owners, and finally an activity could be inferred via a decision-making scheme.

We implemented two experiments to evaluate the performance of our method. In the first experiment, we used an ADL dataset from MIT lab. The proposed method was compared to a naïve Bayes approach [22] and three other ontology-based approaches, namely BDS, 2LDS, and 3LDS [5]. The results obtained showed that the proposed method outperforms the naïve Bayes and BDS schemes, having a precision of 84% and an accuracy of 88.9%. However, it had a similar performance, compared to 2LDS and 3LDS. But the proposed method is more extensible and flexible since no manual ontology definition is required. In the second experiment, a larger dataset by VanKasteren et. al. [28] was used, and the proposed method was compared with three approaches based on NBCs, HMMs, and HSMMs. Three features were extracted from the sensors' data and incorporated in the benchmark methods, which made 9 implementations. The simulations showed that our method outperformed the benchmark methods in most of the cases or was comparable to them, having a precision of 86.7% and an accuracy of 94.2%.

The proposed method has two input parameters. The first one is parameter d that determines the number of n-tuple categories, as depicted in sub-section 4.4. This parameter can affect the classification efficiency and complexity. By increasing d, the number of opinion-owners will increase. Thus the beliefs of more opinion-owners are likely to be fused in the inference scheme. This will influence the classification efficiency and time/space complexity of the proposed method. However, we showed that with $d = 2$, the classification performance of the proposed method was comparable to the others through the experiments. The second input parameter is the accept area that determines the frame of opinion-owners for activities. The larger the accept area is, the more opinion-owners are likely to fall within the frame of opinion-owners of an activity. Thus more evidences, though contradicting, would be available for it. On the other hand, if the accept area is strictly confined, then the frame of opinion-owners may become empty, and no evidence may exist for an activity. This will also affect the efficiency of the activity inference scheme. The study of the impact of input parameters on the performance of the proposed method is left as a future work.

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نشریه هوش مصنوعی و داده کاوی

روشی مبتنی بر حسگرها برای شناسایی اعمال در خانه‌های هوشمند با استفاده از نظریه شهود دمپستر-شافر

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چکیده:

در این مقاله روشی برای شناسایی اعمال در خانه‌های هوشمند مبتنی بر حسگرها ارائه شده است. بدین منظور، صاحبان عقاید و توده های باور آنها با استفاده از حسگرها ایجاد، و در یک معماری استنتاج تک لایه‌ای به کار گرفته شده‌اند. توده های باور با استفاده از تابع توزیع بتا محاسبه گردیده‌اند. برای دستیابی به انعطاف پذیری و توسعه پذیری بیشتر، قاب های صاحبان عقاید برای اعمال به صورت اتوماتیک استخراج می‌گردند. روش پیشنهادی با استفاده از دو آزمایش مجزا ارزیابی شده است. در آزمایش اول، روش پیشنهادی با یک رویکرد مبتنی بر رده بند ساده بیز و سه رویکرد مبتنی بر هستان شناسی مقایسه شده است. روش پیشنهادی با میزان درستی ۸۸/۹٪ در مقایسه با رده بند بیز، عملکرد بهتری را نشان می‌دهد. هرچند، در مقایسه با رویکرد های مبتنی بر هستان شناسی، کارآیی روش پیشنهادی مشابه و قابل مقایسه می‌باشد. اما از آنجا که در روش پیشنهادی تعریف هستان شناسی ها به صورت دستی انجام نمی‌شود، انعطاف پذیری و توسعه پذیری بیشتری را نسبت به روش‌های قبلی دارد. در آزمایش دوم، مجموعه داده بزرگتری به کار گرفته شده، و روش پیشنهادی با سه رویکرد مبتنی بر رده بند ساده بیز، مدل مارکوف مخفی، و مدل مارکوف نیمه مخفی مقایسه گردیده است. در این آزمایش، روش پیشنهادی درستی ۹۴/۲٪ را نشان می‌دهد، که در بسیاری از حالات بهتر از روش‌های مورد مقایسه بوده، و یا با آنها قابل مقایسه است.

کلمات کلیدی: شناسایی اعمال، نظریه شهود دمپستر-شافر، خانه‌های هوشمند.