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Evidential Sensor Data Fusion in a Smart City Environment

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Abstract

Wireless sensor networks have increasingly become contributors of very large amounts of data. The recent deployment of wireless sensor networks in Smart City infrastructures have led to very large amounts of data being generated each day across a variety of domains, with applications including environmental monitoring, healthcare monitoring and transport monitoring. The information generated through the wireless sensor nodes has made possible the visualization of a Smart City environment for better living. The Smart City offers intelligent infrastructure and cogitative environment for the elderly and other people living in the Smart society. Different types of sensors are present that help in monitoring inhabitants' behaviour and their interaction with real world objects. To take advantage of the increasing amounts of data, there is a need for new methods and techniques for effective data management and analysis, to generate information that can assist in managing the resources intelligently and dynamically. Through this research a Smart City ontology model is proposed, which addresses the fusion process related to uncertain sensor data using semantic web technologies and Dempster-Shafer uncertainty theory. Based on the information handling methods, such as Dempster-Shafer theory (DST), an equally weighted sum operator and maximization operation, a higher level of contextual information is inferred from the low-level sensor data fusion process. In addition, the proposed ontology model helps in learning new rules that can be used in defining new knowledge in the Smart City system.

Type of Paper and Keywords

Regular research paper: *Wireless sensor network, Smart City, context-aware reasoning, activity recognition, sensor fusion, ontology*

1 Introduction

In recent years there has been an increasing trend of large numbers of people moving towards urban living. As forecasted in [21] by 2030 more than 60 % of the population will live in an urban environment. Some of the systems that can address the challenges related to increased population will contribute to the development of the Smart City. The Smart City concept operates in a complex urban environment, incorporating several complex systems of infrastructure, human behaviour, technology, social and political structures and the economy. A Smart City provides an intelligent way to manage components such as transport, health, energy, homes and buildings and the environment. The data generated by these components is primarily by wireless sensor networks. Wireless sensor networks have been deployed in many industrial and consumer applications such as health monitoring, smart home applications, water and environmental monitoring.

Sensor nodes associated with different Smart City applications generate large amounts of data that are currently significantly under-used. Using existing ICT infrastructure, generated heterogeneous information can be brought together. Some of the existing wireless communication technologies that can be exploited to achieve information aggregation are 3G, LTE and Wi-Fi. In the context of usage of embedded devices and existing internet infrastructure, the Internet of Things (IoT) encompasses personal computers and other surrounding electronic devices. The Smart City vision is dependent on operating billions of IoT devices from a common place.

The recent emergence of low power wireless network standards for sensors and actuators has enabled administrators to manage and control a wide range of sensor networks and actuators remotely. In order to facilitate the interaction between wireless sensor networks and Information and Communication Technologies (ICT), initially a Smart City architecture is proposed [11]. The plan is to deploy the architecture on a service platform. Through this platform, sensor applications can be connected and utilized by different web applications for an intelligent operating condition.

In addition, we propose a generalized Smart City ontology model, which is presented in Section 5. This model will help in semantic exploitation of collected information for the different Smart City domains. The proposed ontology model helps in efficiently dealing with the information uncertainty and data heterogeneity aspects in the Smart City environment. Semantic web technologies [1] play an important role in the ontology design process as they enable the timely exploitation of domain specific information in the form of concepts and relationships. Semantic web technologies such as Resource Description Framework (RDF) [3], Web ontology language (OWL) [1] and Simple Protocol and RDF Query Language (SPARQL) [8] allow linking of concepts obtained from large volumes of heterogeneous sources in a meaningful manner.

In addition, the uncertainty aspect of the Smart City semantic model will be addressed through the Dempster-Shafer (DS) [26] reasoning approach. Dempster-Shafer theory (DST) [5] allows us to extract new knowledge in the form of rules for activity recognition. Existing data fusion approaches tend to be in a single domain, such as health [4], and vehicles and traffic [16]. Moreover, only some of the approaches are automated, and they are also limited to their respective domains. We use the DS reasoning approach not only for dealing with data uncertainty and partial data fusion but also for learning new rules that will be utilized in defining new knowledge in the Smart City semantic model. For example, the use of DS combination rules to combine sensor information from the home and environment domain can enable us to recognize activities such as eating breakfast in the Smart Home domain, or to recognize the emergence of scenarios that might require management or intervention.

To summarize, through the proposed Smart City ontology model, we will provide essential functionality towards multi-domain sensor data fusion. In our approach, initially the heterogeneous data (sensor data or data from a database) is collected from different Smart City domains and exploited with semantic web technologies. Once the information is semantically enriched based on domain experts' knowledge, it can be further aggregated with other domain data using mathematical combination operators such as the Dempster Shafer combination rule [5], an equally weighted sum operator [17] and maximization operation [28].

The process of information fusion helps in recognizing an activity in a particular domain of interest. Information fusion from one or more domains (e.g. environment, vehicle) with other domain specific information (e.g. home, health) will be on the basis of domain expert knowledge. Once the information fusion process is complete, rules governing a particular activity (e.g. sleeping, eating, driving, running) in a particular Smart City domain are learned and stored. Rules from the above fusion process will help in defining knowledge in the Smart City model. The proposed system will help citizens to manage their lives better and provide government with a useful tool for planning and resourcing. For example, Alzheimer's patients and elderly people with cognitive impairment and memory difficult can be assisted in recognizing their activity in the form of alerts and warnings.

The rest of the paper is organized as follows. Section 2 briefly describes related work and presents some of the proposed novel features of our approach. In Section 3 different evidential fusion approaches (such as Dempster-Shafer combination rule, equally weighted sum operator, and maximization operator) are discussed in detail. Section 4 describes the multi-level Smart City architecture. A detailed generalized Smart City ontology model is presented in Section 5. Section 6 gives a brief description of the graphical notation used in the Smart City ontology model. A case study using our Smart City ontology model is presented in Section 7 with discussion of results in Section 8. Finally, Section 9 concludes and describes future work.

2 RELATED WORK

In a Smart City, wireless sensor networks are the major sources of heterogeneous information generation. The information generated by different sensors often overlaps and is partial in nature. Addressing the challenges related to the fusion of partial data is a research challenge. The DST of evidence, originally proposed by Dempster [5] and then extended by Shafer [22] is an extension of traditional probability and can be used for uncertain reasoning under these circumstances. Tazid et al [23] considers the merits and demerits of different combination rules (such as the Dempster rule, Yager rule, Sun rule) that are used in sensor data fusion. Yoon and Suh [27] and Javadi et al [14] use the DS approach, or uncertain reasoning, for sensor data fusion in the environment domain. The proposed data fusion approaches were limited to the devices and their functionality for a single Smart City domain only.

Similarly, semantic web technologies play an important role in addressing the syntactic (i.e. providing a common format that is capable of addressing different types of sensor readings) aspect of the wireless sensor data. Much research work has already been done in the direction of semantically linking the sensor datasets and inferring knowledge, for example, use of a semantic-based approach in the environment domain [15] and in vehicle localization [19] for inferring high level context information. Berges [2] proposed a canonical ontology-based approach to achieve semantic interoperability for electronic health records (EHR). The proposed ontology is semantically defined on EHR-related terms. Their semantic description is independent of the technology and terms used. It exploits the existing semantic technologies and propriety models in the healthcare domain and links their definition with the canonical ontology. Fensel and Rogger [10] presented a semantic approach to enhance security at a port. Using an ontology-based approach an architecture is presented that aims to reduce noise in sensor data, cope with data heterogeneity, pattern detection and data fusion to provide real-time decision support in the future.

Similarly Jung [15] presented semantic-based data mining in the smart building environment to detect useful patterns and knowledge of the system. Through the proposed ontology-based approach, temporal statistics of the sensor data were defined which further helped in correct session identification as well as in error detection. Through the experiments, it was shown that with correct pattern detection, the contextual sequence of the people in a particular environment can be detected. Ramar [7] presented a service-oriented architecture (SOA) model that helps in defining sensor data semantics and interoperability for disaster management operations. To achieve sensor interoperability, the approach used the Open Geospatial Consortium (OGC) Sensor Web Enablement (SWE) framework. The proposed architecture envisaged integration of low-level information originating from tide gauges, Bottom Pressure Recorder (BPR) and seismic stations using a web based service.

Lecue [16] presented semantic traffic analytics and a reasoner for a city called STAR-CITY. The paper used heterogeneous sensor data obtained from machines and humans to provide real-time traffic conditions in an urban environment. The proposed system was analyzed, explored and diagnosed with different traffic conditions using semantic web technology. Similarly, Florian et al [6] came up with a local danger warning system that utilizes onboard car sensors. They also came up with a classification schema which was based on the situation of the smart vehicle, but their application was limited to the vehicle domain only.

Michael and Christian [9] presented an automotive ontology model in the car domain by utilizing the in-car domain knowledge and user perspective information. Although the ontology design covers detailed aspects related to the car domain, they have not provided any practical scenario in which it can be implemented. Moreover, the proposed ontology covers only the vehicle domain. Towards the Smart home domain, Xin et al [12] proposed an evidential sensor data fusion approach in the Smart Home domain. The proposed approach utilized different information modeling methods such as DST, and maximization operations in inferring high-level contextual information. This approach was limited to Smart home activities. Moreover, it is not discussed how this approach will handle information uncertainty in other domains.

The semantic approaches discussed above tend to limit themselves to their respective domains only. Some of the projects in the direction of multi-domain information fusion include the IBM project SCRIBE [24], defining the Smart City in terms of a semantic model based on data gathered from around the world. The SCRIBE ontology was defined using open standards such as Common Alerting Protocol and the National Information Exchange Model (NIEM). Similarly, the Smart Santander project [29] aims to evaluate the key building blocks of the IoT, which are mainly the interaction and management protocol mechanisms.

In the Smart Santander project, large numbers of sensors will be deployed in different cities and exploited for different applications. The developed test-bed will help in exploiting various Smart City domains such as environmental monitoring, traffic intensity pattern monitoring and guidance for drivers on available parking spaces. The City Sense project [18] aimed to improve existing human infrastructure and thus helps in providing better services to citizens by exploiting available resources (such as electricity, water, and transport) in a more efficient manner. However, these Smart City projects do not provide detailed information about their implementation. In addition, their semantic models do not specify how they will incorporate the uncertainty aspect in their semantic model.

Considering these aspects, our approach will use a multi-level system design, in which low-level raw information is semantically enriched and inferred by intelligent customized applications in a Smart City domain. Furthermore, our sensor fusion approach is based on domain expert knowledge and a reasoning process that uses the DS theory of evidence. One reason of for using DS theory of evidence rather than more traditional probabilistic fusion approaches such as the Bayesian model is because it provides a straightforward way to deal with situations related to missing values, which are common in sensor data. Another problem with the Bayesian fusion method is that priori probabilities need to be calculated in advance. DS is basically a generalization of traditional probability which allow us to better quantify under uncertainty, as it provides bounds on uncertainty through the belief and plausibility functions. In addition, as a Smart City domain deals with data from different domains, under such circumstances DS is very useful in dealing with situations related to fusion of data from multiple independent sources, typically a large range of different sensors.

Finally, rules governing high-level contextual activity will be learned and utilized for defining knowledge in the Smart City ontology model. The proposed model is a generalized ontology model which can be used in the Smart City domain to represent uncertainty, address the information fusion process and learn rules. The Smart City ontology helps us to aggregate different activities and sub-activities based on the behaviour. Thus our proposed ontology provides a powerful solution to the Smart City problem where information is combined from large numbers of Smart City domains such as health, vehicles, the environment, and the home.

3 EVIDENTIAL FUSION OPERATORS

This section defines DST of evidence along with some of the mathematical operators that will be used for different types of heterogeneous information fusion.

3.1 Dempster-Shafer Theory of Evidence

The Dempster-Shafer theory (DST) of evidence is a mathematical theory that allows evidence to be represented in a way which facilitates inference. It was originally proposed by Dempster [5] and extended by Shafer [22]. DST has found its application in various domains such as sensor fusion, biometrics, decision support, medical diagnosis and activity recognition. It is a generalization of traditional probability, which allows better evaluation of the data under uncertainty. It is also known as the theory of belief functions. Belief is a hypothesis and calculated as the sum of the masses of all sets it encloses. Briefly, it facilitates combining evidence from different sources and arriving at a degree of belief (represented by a belief function) that takes into account all the available evidence. We will use the DS approach for heterogeneous information fusion in different Smart City domains.

DST is particularly useful as it allows us to combine data from different sources which may be at different level of detail. The DS combination rule is utilized in inferring a high level context activity (such as Breakfast, Lunch or Snack activities) in the Smart home domain (Figure 6) by utilizing low-level sensor information fusion. The proposed Breakfast ontology model highlights the importance of information fusion in the case of uncertainty (for example, sensor data from a Cooktop object can be aggregated using the DS combination rule in the case of the Breakfast activity). The theory is based on the following mathematical definitions.

The Frame of Discernment (FOD): FOD is a set of mutually exclusive and exhaustive hypotheses. It can also be stated as the collection of finite non-empty sets that are generated as an outcome of an observable event. For example, a sensor might have only 2 active states; in the case of the cooktop sensor the two states are: active ($S_{cooktop}$) and non-active ($\neg S_{cooktop}$). These two values define the set of mutually exclusive values that a sensor can hold:

$$X = \{ S_{cooktop} , \neg S_{cooktop} \} \tag{1}$$

Therefore, the power set, which is the set of all possible outcomes, including the empty set ($\emptyset$), is given by 2^X:

$$FOD = 2^X = \{\emptyset , \{ S_{cooktop} \} , \{\neg S_{cooktop} \}, X\} \tag{2}$$

There are many factors that are important in assigning the mass function values to a sensor event. Due to the uncertain nature of the sensor observation, DS theory assigns values in the range [0, 1] to denote the degree of belief in an active sensor state. This distribution of degree of belief over the FOD is called the evidence, which should satisfy the following conditions:

$$m(\emptyset) = 0 \tag{3}$$

$$m(H) = 1 \tag{4}$$

where m is the mass function, $\emptyset$ is the empty set, and H is a subset of Ω.

The mass value can be assigned to either X or to a subset of the FOD. Thus this property helps the DS theory to better quantify under the circumstances when there is no strong evidence towards a single active sensor. By assigning the total belief to the whole FOD (i.e. m(FOD) = 1) and distributing belief values to subsets of FOD, this theory gives a powerful way to deal with the situation of uncertainty in sensor data.

Belief and plausibility: DS theory gives a useful way to deal with situations under uncertainty. Rather than assigning total probabilistic mass to a single sensor event, it assigns a range of probability values to the sensor event. The lower bound of probability is called the belief, which is given by

$$Bel\ (A) = \sum_{B \subseteq A} m(B) \tag{5}$$

Where Bel (A) is the total belief for which the evidence supports the event A. Similarly, the upper bound of probability is called the plausibility and is given by

$$Pls\ (A) = \sum_{B|B\cap A\neq\Phi} m\ (B) \tag{6}$$

As discussed above, the probability value assignment in the Dempster Shafer combination rule gives a belief distribution over the FOD. When we have several belief distribution values from multiple sources over the same FOD, a new belief distribution value can be calculated using this Dempster-Shafer combination rule. According to this DST of combination, the mass function is thus obtained as a result of a combination of two independent sources in accordance with the following relation:

$$m_{DS}\ (H) = \frac{m_{12}\ (H)}{1 - m_{12}\ (\Phi)} \tag{7}$$

and

$$m_{12}\ (H) = \sum_{\substack{H1, H2\, \in\, 2^{\theta} \\ H1\, \cap\, H2\, =\, H}} m1\ (H1)\ m2\ (H2) \tag{8}$$

where $m_{12}(H)$ represents the conjunctive consensus operator and $m_{12}(\emptyset)$, represents the conflicting mass of the combining sources. Two sources are completely conflicting if their conflicting mass is equal to 1, which means that their masses cannot be combined using this theory.

Here the proposed sensor fusion approach is extension of [12] which was limited to smart home domain only. In our approach we have used the DS combination rule for combining data at different level of detail in a Smart City environment. Usage of the DS rule depends on the nature of the data while combining with other domain data. For example, in the case of a Breakfast activity, if the Cooktop object is used at some instance, then the corresponding sensor data can be fused using the DS combination operator. To summarize, when the low-level sensor data is independent of the high-level context activity, then the DS combination rule can be applied for information fusion.

3.2 Equally weighted sum operator:

This is used when the belief data inputs do not satisfy the condition of being independent, so the sub-activities cannot be aggregated by using Dempster's combination rule. It is given by the following relation:

$$m(A) = m_1 \oplus \ldots \oplus m_N\ (A) = \frac{1}{N} \sum_{i=0}^{N} m_i\ (A) \tag{9}$$

It was first proposed by McClean and Scotney [17] for calculating sum belief for such as a composite node. This type of operation is normally used when the high-level context activity is dependent on the low-level data, under which circumstance the DS fusion process is not valid.

3.3 Maximization Operator

Inspired by the union operation of membership functions in fuzzy set theory [28], this operator is based on the following belief relations:

$$Bel(C) = max\ (Bel(A), Bel(B)) \tag{10}$$

and

$$Pls(C) = max\ (Pls(A), Pls(B)) \tag{11}$$

We use the maximization operator to calculate the aggregated belief values for an activity formed from its alternative sub-activities. The information fusion approaches described above play an important part in dealing with situations related to information uncertainty. The selection of a particular operation is based on the nature of the object/sub-activity/activity. These formulae help in aggregating sensor data from different Smart City components. The next section presents some of the components in the Smart City environment.

4 SMART CITY ARCHITECTURE

With the aid of modern wireless technologies and wireless sensor networks, we envisage the future of Smart City systems providing powerful, intelligent and flexible support for people living in urban societies. As shown in Figure 1, we propose a Smart City architecture

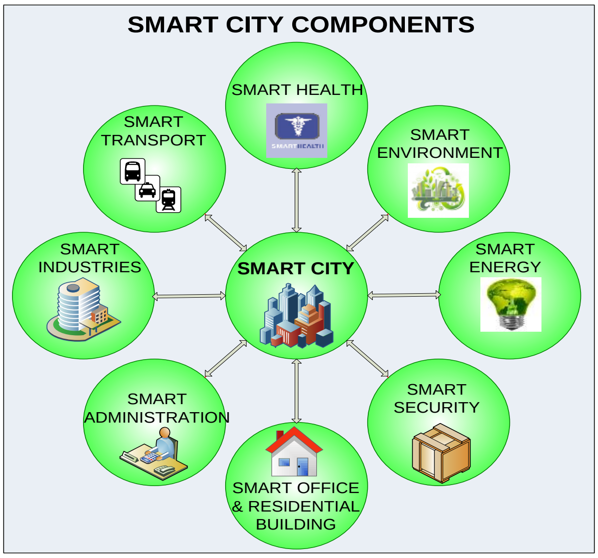


Figure 1: Smart City Components

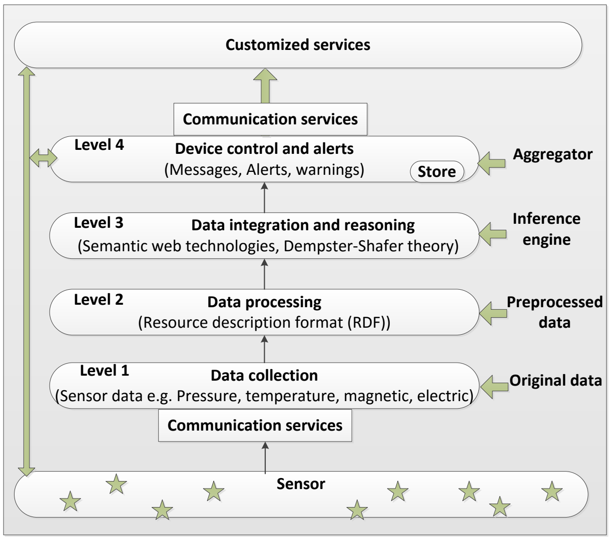


Figure 2: Multi-Level Smart City Architecture

that is an extension of [25], which was restricted to the vehicle domain only. By integrating wireless sensor networks and available wireless communication services, the following research aims are targeted: 1) real-time high-level context-aware customized services; 2) better living environments; 3) improved utilization of the available resources. As shown in Figure 1, we envisage the main elements of the Smart City architecture to be smart health, smart environment, smart energy, smart security, smart office and residential buildings, smart administration, smart transport and smart industries.

The sensor nodes deployed in each Smart City domain provide the primary data source for heterogeneous information generation. The information generated through the sensor nodes is collected using the existing communication services (see Section 4.2). For example, the use of satellite network for GPS devices, cellular services such as GSM/3G/4G for smartphones and the use of the internet for personal computers and other navigation devices for raw data collection. The data collected are then processed and analyzed using semantic web technologies and DS (or other) combination rules. The focus is on deploying the architecture on a cloud platform for use as a software as a service (SaaS).

The proposed architecture can help Alzheimer's patients and elderly people with their daily living activities, for example, by sending alerts and warnings to end users if they forget, or are unable to complete, daily living activities. The system will also serve as an intelligent platform for people living in a Smart society. By combining data from different Smart City domains, the Smart City architecture will help in assisting people in an intelligent manner, for example, guiding a driver to take another route in case of road congestion, alerting heart patients in situations where their heart rate is exceeding a threshold limit while performing an activity, or assisting people with alerts and warnings for their household items such as sending alerts for buying food items.

The implementation of the architecture will follow the steps outlined below. Firstly, the raw data are collected and processed to make them web consumable. Once the data are converted into a common format they are then semantically enriched with OWL concepts based on the knowledge of domain experts. At the same level, the data collected are processed using the DS combination rules to deal with the uncertainty aspects of the semantic model. The purpose is to recognize the activity and learn new rules that govern an activity. The new rules learned at this level will be used in defining the knowledge of the semantic model. The same approach will be used in defining customized services that will provide feedback to the end users (citizens) in the form of alerts and warnings as mentioned in Level 4 (section 4.1.4) of the Smart City architecture.

4.1 Multi-level Smart City Architecture

As shown in Figure 2, sensors form the primary source of information generation. The raw data sensed by a sensor node are transferred to Level 1 of the Smart City architecture using communication services to perform further information processing. A detailed description of each Level is provided below.

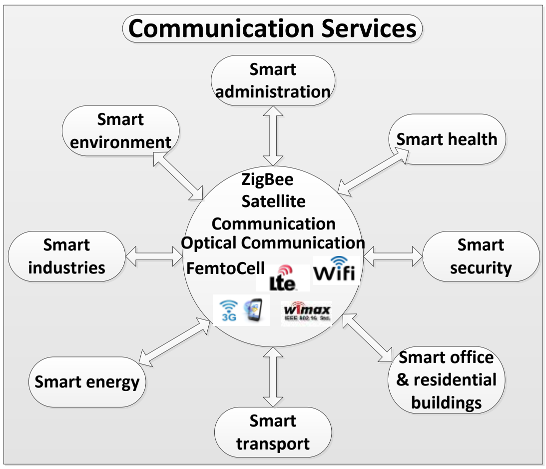


Figure 3: Communication Services

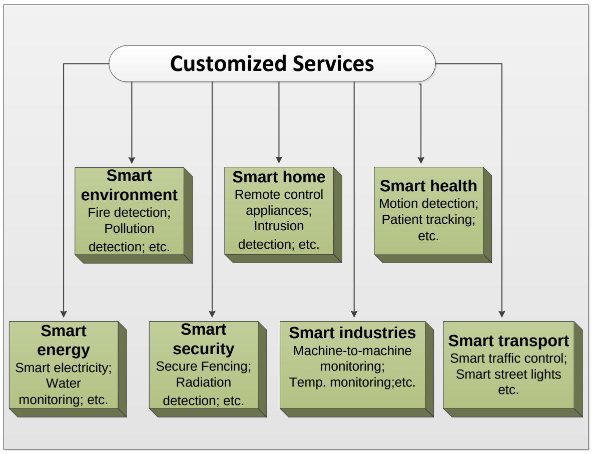


Figure 4: Customized Services

4.1.1 Level 1: Data Collection

In this level, raw information collected from sensors is stored for further processing. Some of the formats in which heterogeneous data are collected are csv, tweets, database schemas and text messages. The formats collected are then processed using semantic web technologies in order to convert them into a common format. The next level describes the steps used in the conversion of data into a common format.

4.1.2 Level 2: Data Processing

Information gathered from the data collection level is summarized prior to transmission, analysis and fusion in the further levels using semantic web technologies. The main objective of this level is to convert the collected heterogeneous information into a common format, e.g. Resource Description Framework (RDF). RDF [3] is the most common way to exchange information over the web and it facilitates heterogeneous data sharing and integration for different Smart City domains. RDF also helps in defining metadata about the resources on the web. Different software applications can then utilize RDF data for intelligent reasoning operations. Pre-processed RDF data generated at this level will be exploited using semantic knowledge and uncertain reasoning rules in the next level for high-level context-aware information retrieval.

4.1.3 Level 3: Data Integration and Reasoning

Semantic web technologies enable exploitation of domain-specific data based on the concepts and relationships between those concepts. The techniques used are summarized below.

Web ontology language (OWL) [30] is used for publishing the ontologies. It allows the classification of individual concepts based on the classes. It also provides two different types of properties, which can be used to form relationships between different classes, namely the Data property and Object property. Once data classification is done, knowledge can be further enriched by domain experts and uncertain reasoning.

Dempster-Shafer Theory will be used here for activity recognition and learning new rules in a particular domain of discourse. In this paper, the DS approach is used for combining sensor data from different Smart City domains such as Smart home [14] and Smart vehicle domains [19]. The proposed approach will help in learning new knowledge through uncertain reasoning and thus assist in achieving an intelligent system.

SPARQL is an RDF query language [8] that is used to query, retrieve and manipulate data/records stored in the RDF format. Once the whole database is expressed in the form of RDF triples, SPARQL enables the query and retrieval of data in the same format. Therefore, this level facilitates low-level information fusion. The new rules learned during the process of extraction of high-level context information from raw sensor data can then be stored and used for building up knowledge in the Smart City architecture.

4.1.4 Level 4: Device Control and Alerts

Data obtained from Level 3 can be utilized by different web applications for intelligent operating conditions. The inferred data can be utilized in many ways such as input/output, messaging, alerts and warnings [7].

4.2 Communication Services

The communication medium plays an important role in achieving the Smart City concept. Figure 3 shows the existing communication services that are utilized in a Smart City infrastructure: 3G (3rd generation), LTE (Long-term evolution), Wi-Fi (Wireless fidelity), WiMAX (worldwide interoperability for microwave access), ZigBee, CATV (cable television) and satellite communication. The main aim is to connect all sorts of things (sensors and IoT's) that can help in making the life of citizens more comfortable and safer. An example is provided by communication services in the home domain for connecting telephone devices and personal computers through the Internet. In the case of the Government sector, cloud and communication services are combined to obtain a better governance system. In the case of the health sector, communication technologies can be used to connect health statistics, medication and location of the patient from a remote location and thus help to achieve a Smart Health system. Hence, with Smart City and communication technologies we can provide a more secure and convenient infrastructure for better living.

4.3 Customized Services

Figure 4 shows some of the customized services in the Smart City environment. For example, in the case of the vehicle and health domains, by combining sensor data we can measure the impact of driver health parameters on driving conditions. Combining health parameters like blood pressure and heart rate with vehicle status can help the driver to measure their real-time health condition, which can help in creating a safe environment for drivers.

Similarly using vehicle location, vehicle speed and volume of traffic approaching a junction, we can help in better monitoring of vehicle status. In the case of the healthcare domain, information collected through wireless sensor networks about patient health and activity can assist a disabled person. Similarly, by combining the home and environment domain data, the effect of temperature on home activities like eating, bathing, sleeping and cooking can be learned. This can help in recognizing correct activity status, which in turn can be a useful care tool for the elderly and people suffering from dementia.

In the case of the environment and administration domains, the low-level information collected from the environment domain, such as temperature and water level, will help in deriving high-level customized information. When high-level customized information (such as flood, earthquake, forest fire, landslide and other natural calamities) is combined with city administration services, it could help in saving lives. Similarly, in the case of the industrial sector, context-aware services obtained through heterogeneous data fusion will help in creating a safe working environment for factory workers. By continuous monitoring, recording and analyzing of the ambient sensor information from different domains (such as harmful gas detection, machine conditions and workers' health) in an industrial environment, a more productive and safer environment for workers can be created.

As described in Level 3 of the multi-level Smart City architecture, this particular layer forms the inference engine of the Smart City system. All the information processing and reasoning will be done at this level of the Smart City architecture. Semantic web technology, together with information modeling methods such as DST, equally weighted sum operator and maximization operation, is exploited to achieve a smarter system. The following section gives a detailed description of the generalized ontology model in the Smart City environment. The proposed Smart City ontology model helps in the timely exploitation of domain-specific concepts and inference of new knowledge for a smarter system.

5 SMART CITY ONTOLOGY: DESIGNS AND CONCEPTS

Ontologies are used to design and formalize high-level concepts using simple detailed descriptions. Ontologies allow us to better quantify the relationships in the Smart City environment with the help of concepts and relationships between them. Ontologies also allow sharing of the information with different objects in the Smart City environment. They enable the creation of a logical model in the Smart City domain that helps in including the objects and associated activities using defined relationships between them.

An ontology with a sparser description will be very easy to understand, whereas detailed ontologies are highly complex and difficult to reason. The design goal of the Smart City ontology model is to avoid the unnecessary details of high-level information and facilitate ease of data fusion with other domain data. Simple ontology design not only helps in achieving easy information exchange, but also allows seamless information fusion from other domains. The Smart City ontology design as shown in Figure 5 is constructed using the following concepts and relationships.

Concepts: Concepts help in defining the entities in the Smart City model. They are used here in the same manner as used in a typical ontology design. They are also called classes in the ontology. They are mainly defined by individuals. Some of the concepts modeled

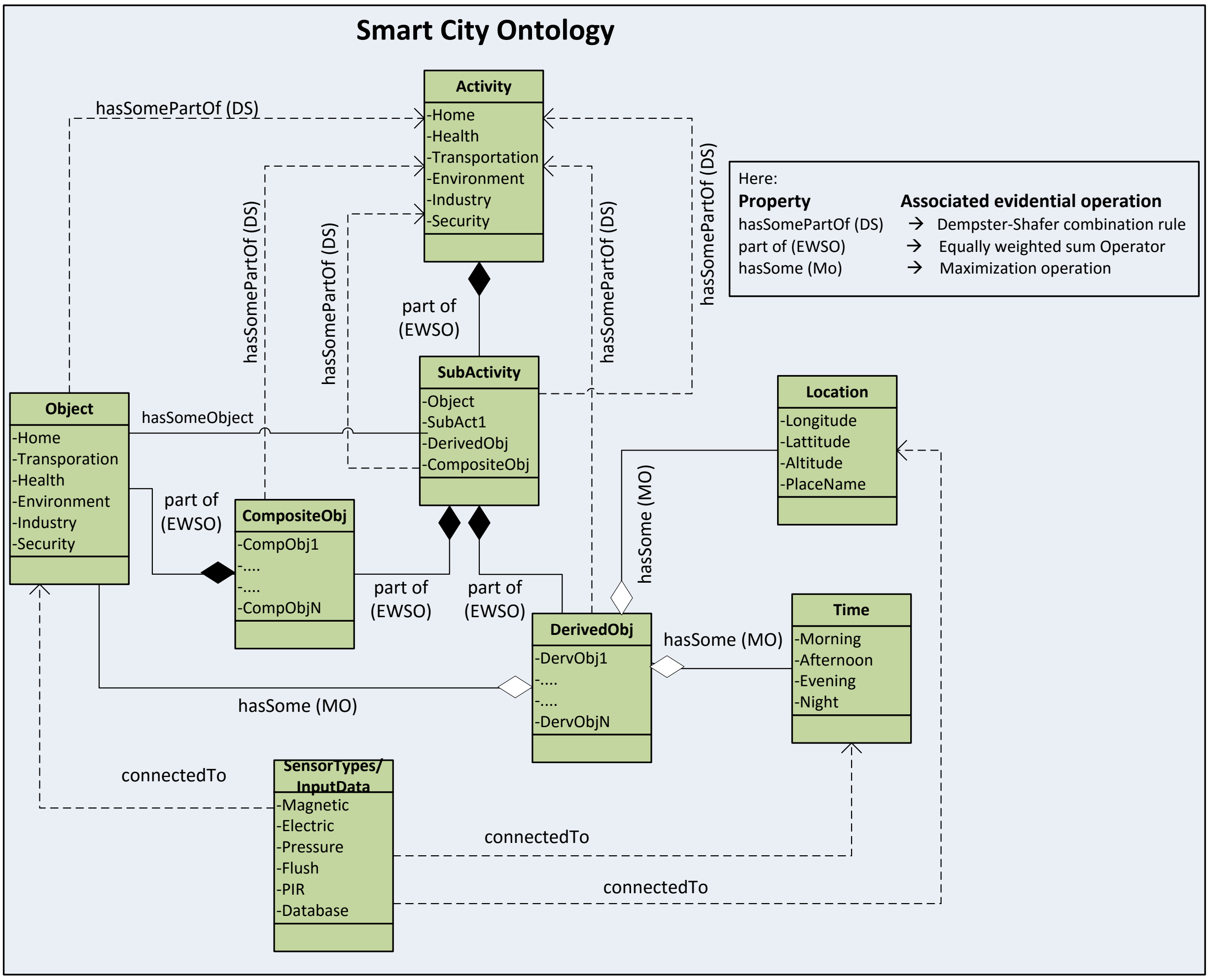
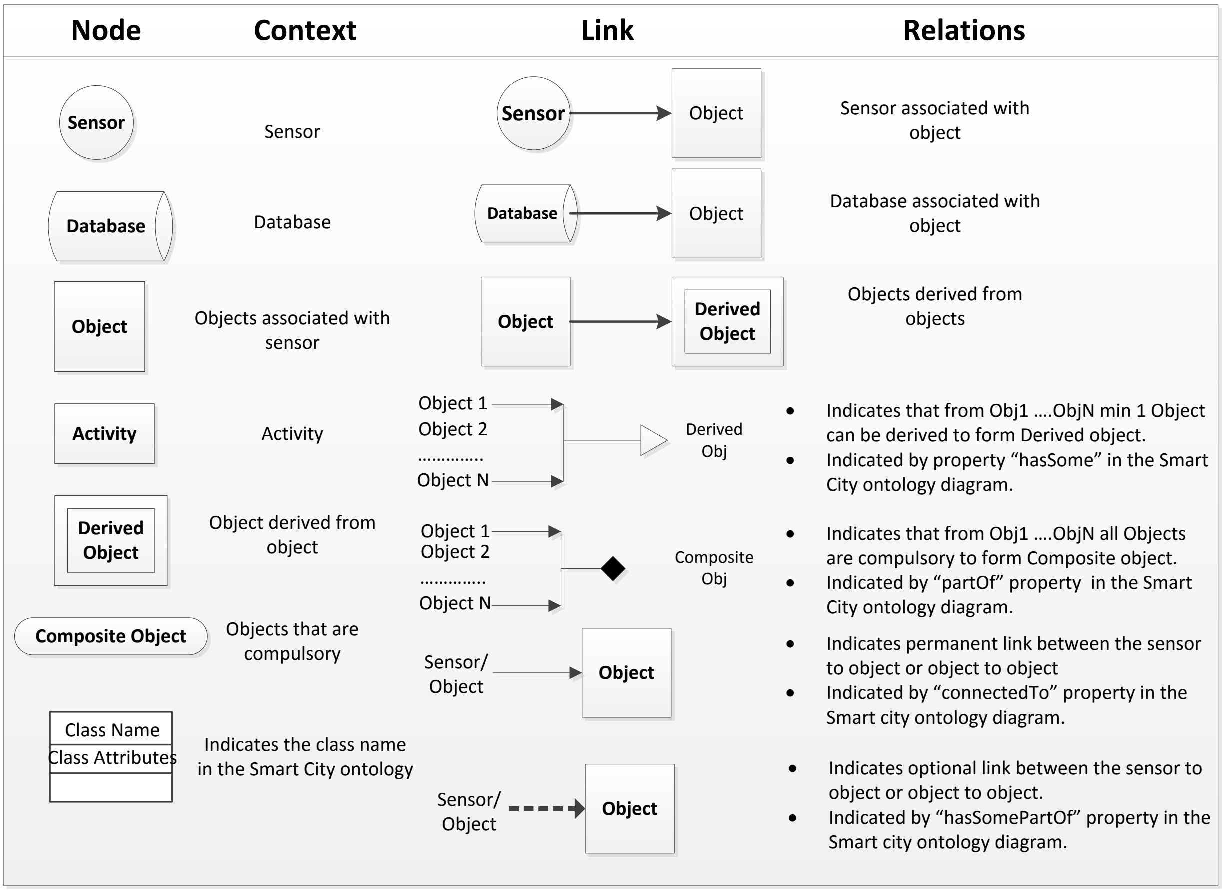


Figure 5: Smart City ontology

in the Smart City ontology as shown in Figure 5 are described below.

Activity class: The Activity class forms the parent class for all the activities/sub-activities/objects. All the final activities in the Smart City environment will reside in this class. For example, in the case of the Home domain the home activities include: Leaving, Toileting, Showering, Sleeping, Breakfast, Lunch, Dinner, Snack, Spare_Time/TV, Grooming, Intrusion Detection. Some of the activities in the case of the Health (personal) domain are walking, climbing, running, jumping, hopping, skipping, marching, and galloping. Similarly in the case of the Vehicle domain activities include smart parking, smart lighting, automatic route detection, and congestion avoidance. In the case of the Environment domain, some of the activities are air pollution detection, earthquake detection, temperature monitoring, harmful radiation detection and forest fire detection. In the case of the Industrial domain, some of the activities include vehicle auto diagnosis, ozone presence detection, indoor air quality measurement, and temperature monitoring. Similarly in the case of the Security and Emergency services domain some of the activities include perimeter control, intrusion detection, radiation level detection, and explosive gas detection.

SubActivity class: The Sub-Activity class contains the collection of the entities such as sub-activities, derived objects, and compulsory objects. This class can be considered as a collection of the intermediate classes that may result in the final Activity class. For example, Sub-activities in the case of the Health domain can be formed from the aggregation of different home objects such as fridge, cupboard, cooktop, and microwave for the breakfast activity. Although here the sub-activity itself doesn’t give any useful information about an event/activity, it forms an intermediate step for the final activity. Similarly, in the case of the Health (personal) domain sub-activity can be body posture and motion



detection that helps in inferring higher level activities such as running, walking, and sleeping. In the case of the Vehicle domain, sub-activity could be road blockage detection and vehicle tracking system, which form a high-level activity such as congestion detection and guiding the vehicle to achieve a congestion-free journey.

Object class: The object class contains the collection of Smart objects in the Smart City environment. For example, objects in the case of the Home domain include shower, fridge, microwave, toaster, cooktop, basin, toilet, maindoor, cabinet, cupboard, seat, and bed. Similarly, objects from the Health (personal) domain can be blood pressure monitor, heart rate monitor, weight detector, and motion tracking devices. In the case of the Vehicle domain smart objects could be petrol level indicator, headlight detector, motion detector, position detector for nearby vehicle detection and road monitoring, and position tracker using GPS to track the position of the vehicle. In the case of the Environment domain, some of the smart objects are gas detector, temperature measurement, soil moisture detector and vibration detector devices. In the case of the Industrial domain, some of the objects are Zigbee and RFID tags. In the case of the Security and Emergency services, smart objects include smart fences and liquid detection devices.

Derived object class: The Derived Object class contains the collection of all the objects that are derived from the object class. Examples include selecting tea or coffee for a drink activity from the tea/coffee object in the home domain. Similarly, detecting a single motion like running or walking from the accelerometer sensor object in the case of the personal Health domain.

Compulsory/Composite object class: The Composite object class contains the collection of all the objects that are compulsory for a sub-activity or activity class. Examples are objects such as fridge, microwave, toaster and cooktop, which form the composite/compulsory objects for the breakfast activity in the home domain. Location and vibration detection for early earthquake detection in the case of the Environment domain and GPS device and nearby traffic statistics for a problem-free ride in the Smart Transportation domain are also composite class examples.

Temporal/Spatial class: In the Smart City ontology the temporal aspect of the event is addressed using the Time class and the spatial aspect using the Location class.

SensorTypes/InputData class: This class contains the list of the sensor types or input data used by the end user in the Smart City environment. It is related to other classes such as Object class, Time class and Location class using the dependency relationship. The dependency relationship indicates that object class/Location class / Time class is dependent on the input values which are initiated either by triggering the sensor type or by an input value from the database/end user.

Relationships: Relationships help in defining the relations between the defined concepts or classes.

"Is-a" relation: The Is-a type of relationship helps in defining the relationship in the form of sub-class and super-class. The classes that are defined using the Is-a relationship mainly inherit the concepts and properties of the super-class. Examples include a magnetic sensor: all the concepts and associated properties of the Sensor class are automatically inherited by the Magnetic sensor class. In the Smart City ontology inheritance does not play a major role, but it will be used in categorizing and storing the information in a hierarchical order.

Properties: Properties are used in the ontology design to provide ease of understanding of the relationships between the concepts/classes. They are merely a naming convention that helps in defining a knowledgeable term that links the different classes/concepts in the Smart City. Some of the properties that are used in defining the Smart City ontology are described below.

"**hasSome" property**: The "hasSome" property is used to define a weak form of association with the other classes. The semantics are such that one class is the child of another. It can be annotated with a number of restrictions in order to express the exact relationship of the child class with the parent class. Example: A car hasSome wheels.

"partOf" property: The "partOf" property helps in defining the compulsory events associated with other classes. It helps in defining a strong form of relationship with the other concepts/classes. Subclasses that share this property with the super-class are compulsory entities to the super-class activity for example CompositeObj class and DerivedObj class in the Smart city ontology diagram.

"hasSomePartOf" property: The "hasSomePartOf" property is used in the Smart City ontology to define an optional/weak form of relationship with other classes/objects. The objects/subclasses that follow this property are optional events to the super-class. Their occurrence is uncertain with respect to the occurrence of a final activity in the Smart City environment.

"connectedTo" property: The "connectedTo" property in the Smart City ontology indicates the dependency relationship of an object/sub-activity class with a SensorTypes/InputData class. This property does not have much importance because the attributes under this class are hidden from the external world. The reason for including this form of relationship in the Smart City ontology is to show the dependency of the input state (SensorTypes/InputData) with the object and sub-activity class.

In order to visualize how reasoning in the Smart City model will be accomplished, a use case diagram of the Breakfast ontology is created as shown in Figure 6. The Breakfast ontology is based on information gathered from the Home and the Environment domains. The purpose is to show how we can model the knowledge in the Smart City domain using the semantic model that will be able to address uncertainty using the DST, fuzzy theory and weighted sum operation. The following section provides a description of the graphical notation used in Figure 5 and Figure 6.

6 ONTOLOGY CLASSIFICATION

Sensor data helps in classifying the activity object based on its nature of occurrence. Once a sensor is activated, it helps in inferring a higher event based on the information that is active at that time-stamp. Table 1 gives a summary on the graphical notation used in the Smart City ontology diagram, which is an extension of [12], which was restricted to the Smart home domain only. Based on sensor data fusion from different Smart City domains, these relationship properties will be exploited to achieve a smarter system. Using Table 1 of graphical notations, a generalized Smart City ontology model (Figure 5), as well as an example, is presented in Section 7 (Figure 6).

Based on the description above of the concepts and associated relationships between concepts, the evidential operators used are based on the following properties:

Case 1: *If Class A → (hasSome) → Class B.*

If two classes/concepts are linked using property linkage = "hasSome", then we use the Maximization operation, which is given by the membership function of fuzzy set theory [28]. For example, Temperature classification such as normal, cold and hot in the Smart environment domain follows the maximization operation as shown in Figure 6.

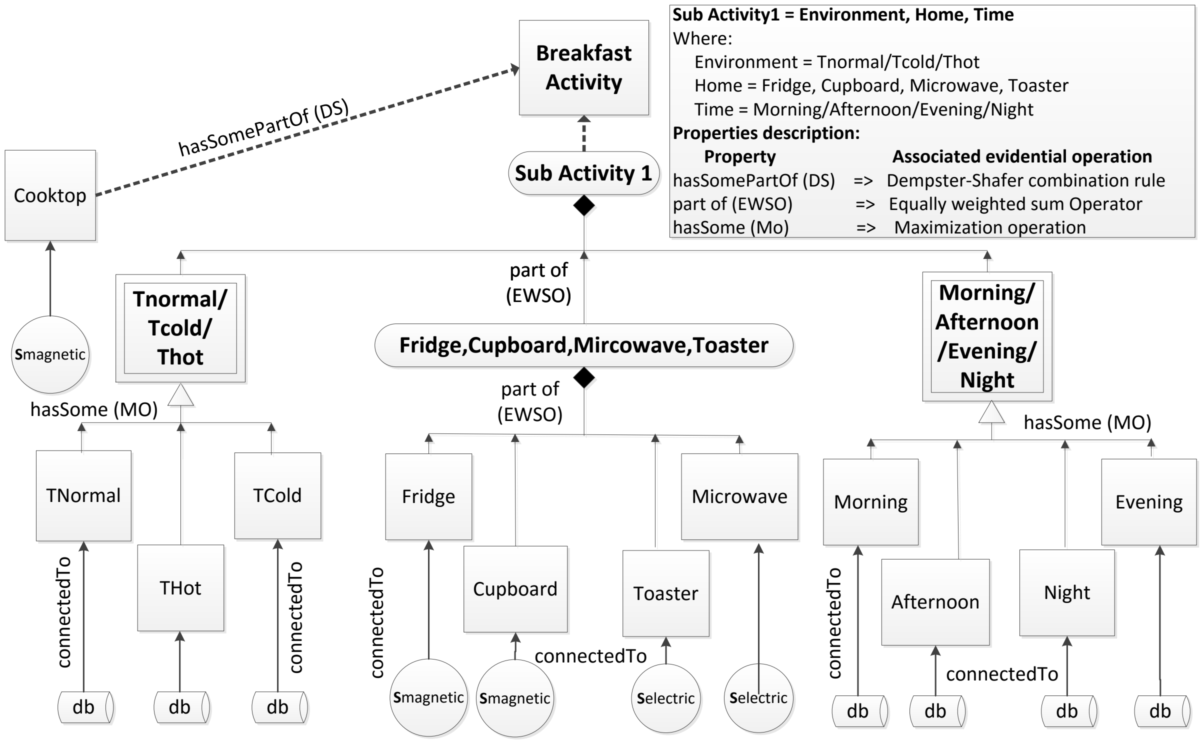


Figure 6: Breakfast ontology

Case 2: *If Class A → (partOf) → Class B.*

If two classes/concepts are linked using the property linkage "partOf", then we use the Equally weighted sum operation [17]. For example, Fridge, Cupboard, Microwave and Toaster objects follow the "partOf" property in the Breakfast ontology (Figure 6), and are thus aggregated using the equally weighted sum operator.

Case 3: *If Class A → (hasSomePartOf) → Class B.*

In this case when two classes/concepts are linked using the property linkage "hasSomePartOf", then the DST [22] operation is used. For example, learning role impact Cooktop object to infer high-level Breakfast activity in the Smart home domain (Figure 6).

7 SENSOR DEPLOYMENT

Sensor deployment in the Smart City involves complexities such as privacy, cost and practicability. Due to these constraints, the proposed research focuses on utilizing existing infrastructure. Often a variety of sensors have been involved in collecting the domain specific data. Binary sensors have been deployed practically and accepted among a wide range of Smart City applications. These sensors do not directly detect the occupants, but they give a binary state for them. Apart from binary sensors, other sensor types include temperature sensors, velocity sensors, and vibrations sensors. Sensor data fusion helps in addressing data heterogeneity aspects of the raw sensor data.

In the Smart City ontology model, the domain expert's knowledge will assist in categorizing the objects/activities. For example, consider the Home and Environment domain information from the Smart City system and learning the impact of temperature on the activity of eating. The domain expert's knowledge helps us in understanding the surrounding domain data that can be combined to infer high-level context information. Based on the low -level data classification as explained in Section 5, low-level information fusion and high-level context information inference can be achieved in the Smart City system. The main intention is to learn new rules through ontology-based information fusion of data from the different Smart City domains.

7.1 Evidential Operations

Based on the dataset that we have obtained for the Home [20] and Environment [31] domains, we have carried out an experiment that will highlight the usage of evidential fusion operations.

Dataset description: Home domain [20] comprises information regarding the ADLs (Activities of Daily Living) performed by a single user on a daily basis in his own home. This dataset comprises of different labelled

ADL's (Activity of daily living) collected by 12 different sensor which are installed in home environment. Some of recorded activities are such as Showering, Sleeping, Breakfast, Lunch, Dinner, Snack etc. Each instance of the dataset is described by sensor events (features) and corresponding activities of daily living (labels). Whereas Environment domain [31] dataset is collected using an online query tool by Microsoft, which allow us to enter the start and end time stamp with the location information and outputs the environment related parameters such as temperature, humidity etc.

Case study: Smart home and Smart environment are two important domains of the Smart City system. When the raw data collected are combined with the information fusion approaches, it will help in deriving high-level contextual information. The derived high-level contextual information will help in learning new rules that can be used for defining knowledge in the Smart Home semantic model in the Smart City domain. Based on the state of the sensor (for example, electric, magnetic) and the input we have obtained from the database, classification of the Breakfast activity is shown in Figure 6. Figure 6 shows that the magnetic sensor is attached directly to the fridge and cupboard, while the electric sensor is attached to the toaster and microwave objects in the Smart Kitchen environment. Similarly, in the case of the Environment domain, data is collected from existing databases. For the sake of simplicity, we have divided the temperature into three different categories, namely Normal, Cold and Hot. Similarly, for the time of day at which events take place, we have categorized events as Morning, Afternoon, Evening or Night.

Based on this object/sub-activity categorization, the Breakfast ontology model is proposed as shown in Figure 6. Once the categorization process is finished, the object/sub-activity is fused based on the mathematical operators discussed below.

7.1.1 Dempster-Shafer Rule of Combination

A belief distribution presents a probability opinion over the frame of discernment. When several belief distributions are obtained through distinct sources over the same frame of discernment, a new belief distribution representing the consensus can be produced by Dempster's rule of combination [23] (as described in Section 3.1.1). In the proposed Breakfast ontology model, the DS combination rule is applied where an Object/Sub-activity is attached to another activity using the "hasSomePartOf" property. For example, in the case of the Breakfast activity, we observe the uncertainty of the cooktop sensor with the composite (Temperature, Home, Day) activity.

7.1.2 Equally Weighted Sum Operator

In the Breakfast activity, the intermediate sub-activity FCMT (fridge, cupboard, microwave and toaster) is the composite of the sub-activities fridge, cupboard, microwave and toaster. All four sub-activities contribute beliefs to FCMT [13] [17] (as explained in Section 3.1.2). This particular operation is applied in the semantic model where an object/sub-activity is attached to another activity using the "partOf" property.

7.1.3 Maximization Operator

``Making Breakfast", ``Making Lunch" and ``Making Snacks" are three alternative sub-activities of the "Eating" activity. Inspired by the union operation of membership functions in fuzzy set theory [28] (as explained in Section 3.1.3), this is used when an object/sub-activity is attached with the "hasSome" property in the Smart City semantic model.

8 RESULTS

Based on the Breakfast ontology model discussed above, we have combined the two different ontologies (Home and Environment Dataset) using evidential fusion approaches. The purpose of the study is to show how this minimal set of sensors can provide an accurate classification for an activity. In addition, accurate activity recognition will help in learning new rules that will help in defining knowledge for our Smart City system. The results clearly indicate that with the inclusion of other domains (Environment domain parameters such as temperature) sensor/activity information helps to provide better activity recognition in the domain of interest (Home domain eating activity).

For demonstration purposes, we have listed only the fusion process for single and three active sensor events only. Other belief values can be calculated for two, four and five active sensor events. Below are the belief values obtained before and after sensor data fusion. The belief values are obtained by aggregating the data (as shown in the Breakfast ontology model) with respect to the assigned property description. This data classification and property selection is based on the nature of the data being aggregated, as discussed in Section 3. These belief values are based on the data fusion experiment carried out over three different activities, namely: Breakfast, Lunch and Snacks.

Table 2: Belief values for Breakfast, Lunch and Snacks Activity based on Single Active sensor

Name	Bel (Breakfast)	Bel (Lunch)	Bel (Snacks)
CASE A: Without Fusion			
1. Cooktop	0.0439	0.2514	0
2. Cupboard	0.1265	0.1109	0.0722
3. Fridge	0.0741	0.0688	0.3433
4. Microwave	0.1415	0.14	0
5. Toaster	0.2288	0	0
CASE B: With Time and Temperature data fusion			
1. Cooktop-Morning-cold	0.5172	0.0781	0.1603
2. Cupboard-Afternoon-hot	0.1665	0.1751	0.5579
3. Fridge-Evening-normal	0.1488	0.0306	0.6059
4. Microwave-Morning-cold	0.493	0.2152	0.1603
5. Toaster-Morning-cold	0.5244	0.0085	0.1603

Table 3: Belief values for Breakfast, Lunch and Snacks Activity based on three Active sensor

Name	Bel (Breakfast)	Bel (Lunch)	Bel (Snacks)
CASE A: Without Fusion			
1. cooktop-cupboard-fridge	0.2757	0.6266	0.4393
2. cooktop-cupboard-microwave	0.3499	0.7454	0.0722
3. cooktop-cupboard-toaster	0.4425	0.4931	0.0722
4. cooktop-fridge-microwave	0.2921	0.6641	0.3433
5. cooktop-fridge-toaster	0.3859	0.3809	0.3433
6. cooktop-microwave-toaster	0.4583	0.5355	0
7. cupboard-fridge-microwave	0.3517	0.5199	0.4393
8. cupboard-fridge-toaster	0.4436	0.2374	0.4393
9. cupboard-microwave-toaster	0.5172	0.3599	0.0722
10. fridge-microwave-toaster	0.4597	0.2757	0.3433
CASE B: With Time and Temperature data fusion			
1. cooktop-cupboard-fridge-Afternoon-hot	0.2595	0.3346	0.6737
2. cooktop-cupboard-microwave-Afternoon-normal	0.3562	0.7908	0.2
3. cooktop-cupboard-toaster-Morning-cold	0.6409	0.294	0.2285
4. cooktop-fridge-microwave-Afternoon-hot	0.265	0.3811	0.6059
5. cooktop-fridge-toaster-Morning-cold	0.6228	0.1047	0.2761
6. cooktop-microwave-toaster-Morning-cold	0.6459	0.3396	0.1603
7. cupboard-fridge-microwave-Afternoon-hot	0.241	0.5233	0.6737
8. cupboard-fridge-toaster-Evening-normal	0.2706	0.2149	0.6737
9. cupboard-microwave-toaster-Morning-cold	0.6252	0.4791	0.2285
10. fridge-microwave-toaster-Morning-cold	0.6054	0.2573	0.2761

Table 2 shows the belief distribution values for the Breakfast, Lunch and Snacks activities when only a single sensor is active. The proposed belief distribution is divided among the two cases: Case A, which gives the belief values without the fusion process, and Case B, which gives the belief values when the fusion process is implemented in the eating activity model. From the resultant belief distribution table, we observe that all the belief values without fusion are less than 0.5, thus gives no strong confidence in the selection of a single activity. However, when the fusion process is implemented into the same scenario, we observe that each row gives a belief distribution of value greater than 0.5, giving stronger confidence in a single activity. Thus, the resultant belief values with the evidential fusion operation (Case B) support stronger detection of an activity than the process without fusion (Case A).

Similarly, Table 3 shows different belief values for the Breakfast, Lunch and Snacks activities when three sensors are active with and without the fusion process. From Case A, we see that only some belief values are greater than 0.5, giving strong support in detecting a single activity. For example, Cooktop-Cupboard-Microwave active sensors give a strong belief for the Lunch activity. However, if we observe the overall pattern we find that these results are confined to a single activity 5 times out of 10, which is quite uncertain.

However, in Case B, using the information fusion process, the resultant belief distribution provides strong confidence in detection of a single activity event. Thus, evidential information fusion helps in evaluating a more compelling belief distribution for a single activity from a group of sensor events. Based on the belief distribution for three different activities (Breakfast, Lunch and Snacks), some new rules have been learned which will be used in defining knowledge in the Smart City semantic model. These new rules will help in providing a strong belief in the Smart City system based on the activities/objects behavior.

1. `cooktop + cupboard + fridge + Afternoon + hot → Snacks Activity`
2. `cooktop + cupboard + microwave + Afternoon + normal → Lunch Activity`
3. `cooktop + cupboard + toaster + Morning + cold → Breakfast Activity`
4. `cooktop + fridge + microwave + Afternoon + hot → Snacks Activity`
5. `cooktop + fridge + toaster + Morning + cold → Breakfast Activity`
6. `cooktop + microwave + toaster + Morning + cold → Breakfast Activity`
7. `cupboard + fridge + microwave + Afternoon + hot → Snacks Activity`
8. `cupboard + fridge + toaster + Evening + normal → Snacks Activity`
9. `cupboard + microwave + toaster + Morning + cold → Breakfast Activity`
10. `fridge + microwave + toaster + Morning + cold → Breakfast Activity`

Although currently the rules learned from the above Home and Environment fusion process are limited to two domains only, the same approach can be utilized across a larger number of different Smart City domains. To summarize, the learned rules from the novel fusion approach will help in defining knowledge in the semantic model for the Smart City system. An example of the use of this system is for Alzheimer patients to remind them of their current activity in the Smart home environment. Currently the approach is illustrated with a limited training dataset. Future work will include validation of the results using both a test and training dataset.

9 DISCUSSION AND CONCLUSIONS

The Smart City concept has been revolutionized and evolved into a new era with recent developments in ICT that combine wireless sensor networks and computer networks. We aim to address some of the customized services in a Smart City environment by using semantic modeling and extended DST. In addition, through the DS approach in our Smart City architecture we aim to address the uncertainty aspect in the Smart City environment. Although it is very difficult to cover every aspect of the Smart City domain, through our proposed architecture we aim to focus on the most important areas of the Smart City environment. Semantic web technologies can be used in addressing the heterogeneity aspect in the Smart City environment. In order to make the available information machine-readable, the information collected is exploited using the Resource Description Framework (RDF). In addition, the SPARQL end point can be utilized by city administrators for data retrieval and high-level information inference in the Smart City system.

In addition, through this research we have introduced a Smart City ontology model that helps in information management within the Smart City environment. We have highlighted the importance of information processing methods such as DST. Equally weighted sum operators and Maximization operators help to deal with the situation of data uncertainty. Using these mathematical operators, the information fusion process at different levels in the Smart City environment can be rolled out. The proposed fusion approaches help in learning new rules that can be utilized in defining new knowledge for the Smart City ontology model.

Through our Breakfast ontology experiment we have proposed an evidential fusion approach through which heterogeneous information fusion is carried out based on the input state of the different active objects/events. Based on the low-level information fusion, higher level activities are inferred based on the belief distribution values. From the resultant belief distribution values, we conclude that the information fusion process helps to achieve stronger detection of a single activity from the group of sensors and facilitates the process of learning new rules

Future work is planned to perform experiments, including discovering real-time heterogeneous information from different Smart City domains, inclusion of semantic web technologies (such as RDF and SPARQL) in the Smart City system, and the use of extended DS combination theory for information fusion and reasoning at different levels of the Smart City environment.

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