Fuzzy Query Propagation in Sensor Networks

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***Abstract*—Query-driven information retrieval aims at supporting users to request and retrieve relevant data from sensor networks. Due to energy and capacity constraints that characterize sensor networks, information retrieval should avoid flooding the network with queries, but rather find the most efficient propagation path that maximizes the recall of relevant data while minimizing the number of sensor nodes being accessed. This is the problem of query propagation, for which numerous approaches for sensor networks have been proposed. Although, one unaddressed issue that remains is the issue of fuzziness of users' queries and fuzziness of sensor data. When crisp criteria are used to express queries and select query recipients during propagation, some sensor nodes that are relevant can be "missed." Therefore, this paper's objective is to integrate a fuzzy semantic mapping mechanism, which has been published in a previous research, into a new, cluster-based fuzzy query propagation approach. The fuzzy query propagation approach avoids the overload of sensor nodes that are near the sink nodes by incorporating a first propagation step towards relevant clusters of sensors, therefore varying the sensor nodes that will have to redistribute the query, followed by an intra-cluster query propagation phase. The approach has been evaluated with a simulation and compared with a crisp version to show the impact of the consideration of fuzziness in the improvement of the recall of relevant nodes while avoiding the increase of propagation cost.**

Keywords - Fuzzy logics, information retrieval, query propagation, sensor networks.

I. INTRODUCTION

Sensor networks are intended to monitor environmental conditions, such as weather, properties of soil and water bodies, vegetation, etc. While sensors are more traditionally used by scientific experts to study environmental and physical phenomena, it is believed that greater public can also benefit from access to sensor data. In this paper, we extend a previous paper on fuzzy semantic mapping that was presented at the SEMAPRO 2011 conference [1] by integrating the fuzzy semantic mapping approach into a new fuzzy query propagation approach for sensor networks.

In order to support improved access, sensor data should therefore be accessed through the Internet, with the help of platforms such as the Geospatial Cyberinfrastructure for Environmental Sensing platform (GeoCENS). GeoCENS is an online platform that enables simplified searching, storing and sharing of environmental and other georeferenced data [2]. In such platform, sensors collect data on a given feature, process these data and forward it to a so-called "sink node," which in turn forwards the data to the application through the Internet. Because all sensor nodes cannot necessarily be connected to the sink node, sensor data must be forwarded from node to node until reaching the sink node [3]. In the same manner, sensor data queries issued by users must be forwarded from the sink node to the nodes holding the requested data (the relevant nodes) through intermediary sensor nodes in the network.

However, because sensors are meant to be small devices, their processing capacity and their source of energy are limited. Also, despite the decreasing cost of sensors, it cannot be assumed that they can be replaced when they run out of power. For example, some sensors cannot be accessed once being set up in their environment (some are buried to measure soil moisture, while others are underwater to measure water temperature, etc.). Therefore, the path chosen to send queries to sensor nodes and to send back data to the sink node must be determined in a way to avoid consuming the energy of sensor nodes; at the same time, the path chosen must enable to reach the nodes that are relevant to the query and retrieve the requested data. This problem is called query propagation.

Numerous approaches have been proposed for query propagation and data collection from sensor nodes. A representative sample of such approach is presented in Section II. The approaches are varying in terms of the data delivery model (whether sensors proactively send data to the sink node according to a pre-defined scheme, or solely on-demand of the user); organization of the sensor network (flat or hierarchical); and criteria for selecting query recipient nodes. However, one well-know problem in GIScience, but that is still unaddressed in query propagation approaches for sensor networks, is the fuzziness of data and queries.

Research indicates that geographical phenomena in particular are fuzzy [4]. For example, where a mountain starts or ends cannot be determined with precision; and whether the vegetation is dense or not is only an imprecise concept. Fuzzy theory, which allows the partial membership of an element into a set (e.g., the set of dense vegetation areas) is widely used to represent geographical phenomena. For example, in [5], fuzzy theory is used to represent fuzzy land cover categories. Similarly, concepts such as spatial relations that are used in users' queries (e.g., close to, around, at proximity, far from) are also fuzzy [6]. Sensor data can also be fuzzy, for example, the location of the sensor can be imprecise or there is a certain level of uncertainty in data being gathered. The fact that sensor data and queries are fuzzy should be taken into account during query propagation. Conversely, it could result in the inability of the approach to retrieve relevant data.

In previous research presented at the SEMAPRO 2011 conference [1], we have presented a fuzzy logic semantic mapping model to compare components of fuzzy ontologies. In this paper, the objective is to apply this approach and integrate it into a fuzzy query propagation approach. The fuzzy semantic mapping theory and mechanism presented in [1] is incorporated into a cluster-based query propagation approach as a way to express fuzzy queries and select query recipient according to fuzziness degree and a fuzzy semantic relations. The fuzzy query propagation approach incorporates a first propagation step towards relevant clusters of sensors, followed by an intra-cluster query propagation phase. The ability of the approach to retrieve relevant information and a comparison between crisp and fuzzy propagation has been evaluated through a simulation.

The content of this paper is organized as follows: the next section presents related work on query propagation in sensor networks. Section III is a brief introduction to fuzzy logics in GIScience and in sensor networks. Section IV presents our fuzzy query propagation approach, while Section V presents an extended version of the fuzzy semantic mapping mechanism. The evaluation of the approach is conducted in Section VI, while conclusion and future work are provided in Section VII.

II. Query Propagation in Sensor Networks

Propagating queries to the relevant sensors of a network is a challenging issue, since a balance between the quality of query answers and the efficiency of the approach must be reached.

Existing query propagation approaches for sensor networks can be categorized according to the data delivery model they rely on, i.e., how the flow of data between the sensors and the requestor is triggered and organized [7]. The first data delivery model is the proactive model. In the proactive model, sensor nodes periodically forward the data they have collected to a server, at a pre-specified rate, or when an event of interest occurs (event-driven model) [3]. Examples of query propagation approaches based on the proactive data delivery model include [8] and [9]. While the approach proposed in this paper could be somewhat easily adapted to the proactive model, in this paper, we focus on the second type of delivery model, i.e., the query-driven model.

In the query-driven model (or on-demand model), data is sent by sensor nodes only when a user queries the sensor network [10]. The problem then is to determine through which path and to which sensor nodes the query should be sent. We assume in the following that the user can access the sensor network through a so-called “sink node,” which is a node of the network that acts as an intermediary between the user (through the Internet) and the rest of sensors in the network [11]. One common approach for query-driven model is the reverse tree model [10][12][13]. In the reverse tree model, the query is broadcasted from the sink node to the nodes of the network. The structure of the tree is built as the query is propagated from node to node, with the sink node being the root of the tree. Sensors send back their data to the sink node following the tree structure. Approaches based on the reverse tree model vary according to the mechanism they rely on for selecting the nodes that will be part of the tree. For example, some approaches are called “attribute-based,” because at each “jump,” the decision about propagation is made based on a match between the attributes specified in the query and the attributes of data collected by the sensors. Examples of such approaches include [14][15][16][10]. The attribute can be, for example, the area where the sensor is located or the type of sensor. One disadvantage of the reverse tree model is that it can be inefficient because it may impose unbalanced energy consumption in the sensor network, since the nodes that are close to the sink forward more data and queries and therefore, use more energy than other nodes that are far from the sink node [10]. One solution would be therefore to avoid that the sink node always sends the query through its immediate neighbors. To address this issue, and to facilitate routing to relevant sensors in general, the hierarchical routing protocols can be helpful. Hierarchical routing protocols divide the network into clusters of sensors [17][18][8][9]. Queries can then be sent directly from the sink node to the designated "leader" of the relevant cluster, avoiding the same sensors to disseminate the queries and collect the corresponding data.

Other types of approaches, called geographical routing protocols, aim at propagating the queries sent by users who are searching for data from sensors in a specific location. These protocols therefore explicitly take into account the location of sensors in the selection of recipient nodes [19][20][21]. The query includes the targeted coordinates; neighbor sensor nodes in the network are actively sharing the information about their respective location. Therefore, when a node receives a query, it sends it to the neighbor node that is the closest to the targeted location. Villalba et al. [3] indicate that several metrics have been used to measure closeness, the most common ones being the Euclidean distance and the projected line joining the relaying node and the destination. However, we note that such routing protocols based on crisp measures do not allow take into account the fuzziness of queries. More particularly, it is very likely that users lack the capacity to specify a precise location of interest, and can only provide an approximation of it [10]. We argue that this is also true regarding thematic or temporal attributes of queries. For example, a user might look for sensors that have observed "temperature around 30°C" rather than exactly 30°C, within a fuzzy period of time. This motivates our proposal of a fuzzy query propagation approach for sensor networks.

III. FUZZY LOGICS IN GISCIENCE AND SENSOR NETWORKS

GIScience researchers such as Couclecis [22] and Zhang and Goodchild [23] have demonstrated that uncertainty should be considered as a kind of knowledge that must be explicitly represented and dealt with. Fuzzy logics, which were proposed by Zadeh [24] to deal with imprecise and vague knowledge, are now widely used in GIScience [4]. For example, [25] uses fuzzy sets to assess the similarity of categorical maps, while [6] have developed an ontology of fuzzy spatial relations to improve the interpretation of images. Fuzzy theory and fuzzy logics are also widely used in sensor networks. For example, [26] use fuzzy logics in a hierarchical clustering protocol for query routing in sensor networks. In this approach, fuzzy logics are used to select the sensor node that will play the role of the "cluster head" (leader) of a sensor cluster. Fuzzy variables used for cluster head selection include energy, centrality, and concentration. Fuzzy logics have also been used to assess the quality of service (QoS) in wireless sensor networks [27]. More specifically, QoS in wireless sensor networks is highly related to energy efficiency and avoiding the congestion of messages at nodes. In [27], fuzzy logics are used to estimate the congestion at nodes in order to facilitate routing messages more efficiently. Fuzzy logics are also used to assess trust in order to distinguish between trustworthy and threatening nodes in wireless sensor networks [28]. In [29], fuzzy theory is used to enable fusion of uncertain sensor data in wireless sensor networks. The approach was designed for the fusion of data coming from sensors that monitor the same property (in this case, luminosity). Other applications exist that use fuzzy theory in the context of message routing in wireless sensor networks [30][31]. [30] propose a solution to avoid the useless propagation of messages to all nodes of the network. In their approach, the transmission area is limited according to a fuzzy threshold value. The fuzzy threshold value is determined by a fuzzy rule-based system that considers the energy and density of nodes. [31] have developed a fuzzy logic controller that allows nodes in the sensor network to compute their capacity to transfer messages based on their battery power level and the type of data being forwarded. Similarly, [32] proposed an energy-aware fuzzy routing mechanism for wireless sensor networks. Despite numerous works using fuzzy theory for sensor networks, to the best of our knowledge, none investigate the use of fuzzy logics to represent the uncertainty of semantics of sensor data and to support semantic-based query propagation. This motivates the approach presented in this paper.

A. Fundamentals of Fuzzy Theory

This section briefly introduces the basic notions of fuzzy sets and fuzzy logics. In classical set theory, elements of a set either belong to a set, or they do not; conversely, fuzzy set theory was developed to deal with the case of partial membership to a set. Each member of a fuzzy set is assigned a so-called membership degree, which value is between 0 and 1, and which indicates the strength of the membership into the set. A null value indicates that the element does not belong at all to the set, while a value of 1 indicates that the element fully belongs to the set. Consider a set of elements called the reference set and denoted X. A fuzzy subset F of X is formally defined with a membership function $\mu_F(x)$; this function associates any element x of X to a value in the [0, 1] interval. All set operations for crisp sets (union, intersection, etc.) have their fuzzy counterpart. The fuzzy implication operators such as Gödel, Gogen and Lukasiewicz fuzzy implications operators are for example used to reason with relations between fuzzy sets [33] while fuzzy composition operators are used to infer membership of an element into a fuzzy set, knowing its membership degree into another related fuzzy set. The operators that will be used in this paper will be introduced in Section V.

IV. FUZZY QUERY PROPAGATION

The data delivery model targeted by the proposed fuzzy query propagation approach is query-driven [3], i.e., the fuzzy query propagation process is initiated by a user who issues a query expressing the characteristics of the data he or she is looking for. Figure 1 illustrates the fuzzy query propagation framework.

The proposed framework is based on the principle of hierarchical routing protocol [3], which advantage is to avoid large traffic overhead and therefore to reduce energy consumption by sensors [10]. In this paper, we assume that the sensor network is already partitioned into clusters of sensors. Each cluster has a gateway node, which is the node responsible for receiving a query and redistributing it to other members of the cluster. Existing research [26] demonstrates that a single gateway node has disadvantages because it can become a single point of failure (e.g., if the selected gateway node runs out of power or becomes dysfunctional). To avoid this problem, the role of gateway node is rotated among several nodes (provided that they have sufficient capacity). The choice of gateway nodes can be done randomly at predetermined time intervals [34] in order to share the consumption of energy. However, in case of failure, the sink node should automatically forward the queries to the next gateway node. To detect failure of the gateway node, we have included a communication protocol where the gateway node sends a notification to the sink node every time it receives a query. Therefore, if the sink node does not receive a notification, it assumes that the current gateway node is not available and rotate to the next available gateway node.

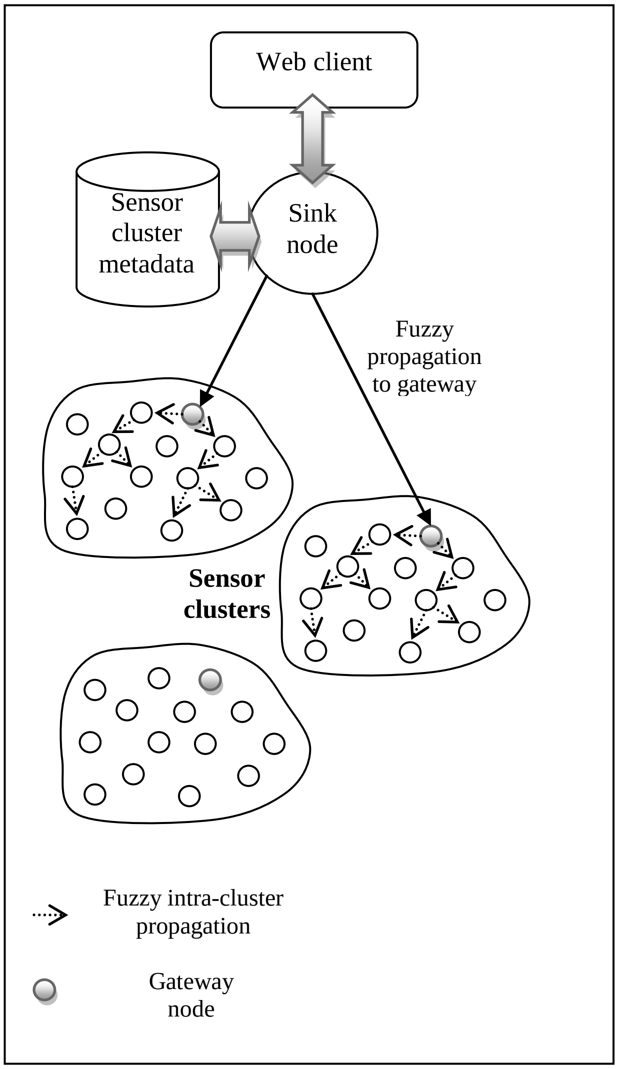


Figure 1. Fuzzy propagation framework

Sensor clusters are formed according to various semantic criteria: sensors which data pertain to similar or complementary domain of application, themes, geographical locations, etc., are gathered into clusters. This facilitates the propagation of queries to targeted groups of sensors instead of flooding the network with queries. Since it is not the objective of this paper to further describe how clusters of sensors are formed, we point out to our previous published research [35] where we have proposed a social-network-analysis-based algorithm for sensor cluster formation. The clustering algorithm identifies, within the available sensors, those that can be considered as "leaders" because their characteristics encompass those of other sensors. For example, a sensor that "measures density of gas" encompasses sensors that "measure density of CO2", "measure density of air pollutant," etc. Leader sensors are identified using the network analysis concept of "centrality." Then, meaningful clusters of sensors are formed around those "leader" sensors. To do so, the algorithm searches the semantic neighborhood of leader sensors to select those that will be part of the cluster formed around this leader sensor.

Each sensor node stores a set of metadata according to the Sensor Model Language (SensorML) format [36]. Similarly, each sensor cluster is associated with metadata that describe the nature of its member sensors. The metadata describe the category of phenomenon observed, the observation period and area of observations, the observed properties (e.g., temperature, soil moisture, etc.), the types of sensors, the intended application and the application domain [36]. The metadata on sensor clusters are stored in a sensor cluster metadata knowledge base, which is held by the sink node that usually has greater storage and processing capabilities than "regular" sensor nodes [10].

A. Global Fuzzy Query Propagation Process

The fuzzy query propagation process is as follows: first, a fuzzy query is formulated by a user. The query is sent, through a Web platform, to a sink node. The sink node is responsible for broadcasting the query to sensors of the network. However, instead of flooding the network, the sink node identifies the clusters that are the most likely to contain sensor nodes that are relevant to the query. To do so, a fuzzy semantic matcher (described in Section V) is implemented at the sink node. The fuzzy semantic matcher compares the fuzzy query with the metadata on the cluster and return matches. Matches are selected according to fuzzy criteria, which computation is discussed in Section V. When matching clusters are selected, the sink node then sends the query to the gateway node of these clusters. Then, the gateway node will initiate the fuzzy intra-cluster propagation of the query, i.e., propagation from node to node inside a cluster.

B. Fuzzy Intra-Cluster Propagation Algorithm

The fuzzy intra-cluster propagation algorithm is provided below in Figure 2. This algorithm is the procedure performed by any node that receives the query during intra-cluster propagation, including the gateway node.

The process starts when a node receives the query. The algorithm performs a sequence of "jumps," from node to node, within the scope of a cluster. "Jump" refers to the action of sending a query from one node to another. The algorithm is parameterized with a maximum number of jumps; the role of this parameter is to avoid the unstopped propagation of the query. Since the algorithm is executed in parallel by several recipient nodes, there cannot be a global maximal number of jumps that can be tracked. Instead, the maximal number of jumps is computed along a single path, i.e., every time the query is forwarded to a node, the current number of jumps is incremented by 1. When a node sends a query to a neighbor node, it also sends the current value of the number of jumps along that path. If a node receives a query but the max number of jumps along this path is reached, it stops the local propagation. Meanwhile, the propagation may continue along other paths.

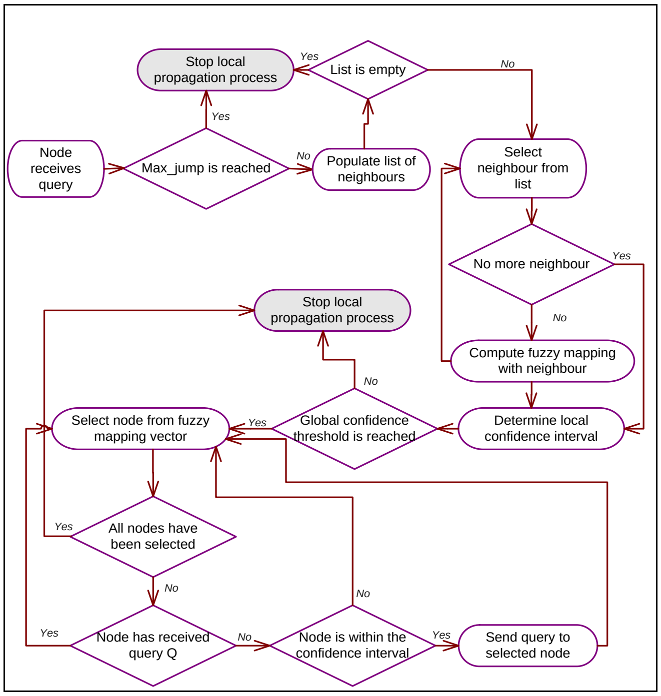


Figure 2. Fuzzy intra-cluster propagation algorithm

If the maximum number of jumps is not reached, the current recipient node creates a list of neighbor nodes. For each neighbor node, the recipient node computes a fuzzy mapping between the query and the neighbor node's metadata, which is composed of two components: a semantic relation r and a fuzzy inclusion value f (details on how the semantic relation r and the fuzzy inclusion value f are computed are given in Section V). As a result, the recipient node obtains a fuzzy mapping vector:

$$V = ((f_1, r_1), (f_2, r_2), \dots (f_n, r_n)).$$

To determine which neighbor node(s) will be selected as new query recipient, three conditions must be verified:

- the fuzzy semantic relation r must be one of the type(s) selected by the user (among the possible semantic relations listed in Table 1 and presented in Section V);
- the fuzzy inclusion must fall within a local confidence interval, and
- the fuzzy inclusion must meet a global user-defined threshold.

The fact that the user can select both quantitative criteria (the fuzzy inclusion thresholds) and a qualitative criterion (the semantic relation r) to restrict the nodes that can be selected as query recipients gives more flexibility to the approach and makes it more adaptable to the user's needs. For example, if the user specifies that the semantic relation between the query and the neighbor node's metadata must be "contains," it means that the user accepts to receive data more specific than the needs expressed in the query. Conversely, if the user select "contained in" as a semantic relation, its means he or she accept to receive data more general than the needs expressed in the query.

The local confidence interval is a percentage of the highest values in V. More specifically, the local confidence interval is the interval of fuzzy inclusion values that contains x percent of the highest values of fuzzy inclusion in V, where x is a threshold that can be user-defined. For example, if x = 20, it means that the interval will contain 20 percent of the elements in V, with these 20 percent elements being the highest possible. Therefore, the smaller x is, the more selective is the algorithm. In the experiment presented in Section VI, we have selected x = 20, since the ability of the algorithm to forward the query to relevant nodes was optimal using this threshold for the given data set.

This interval is local because for every node, a different interval is determined dynamically at run-time. The purpose of having both local and global threshold is to deal with variation of fuzzy inclusion values within the network. To ensure that no node answers twice the same query, the query is given a unique identifier stored by nodes who received it. If a node receives a query it had already forwarded, it will stop the local propagation process (the propagation may continue along other paths).

V. Fuzzy Semantic Mapping Mechanism

In this section, we present the fuzzy semantic mapping mechanism that supports the query propagation process presented in the previous section. The fuzzy semantic mapping mechanism, which produces both qualitative and quantitative relations, was introduced in Bakillah and Mostafavi [1]; however, in this paper we extend it to include the cases of discrete but also continuous properties. Some papers on fuzzy ontology mapping have already been published, for example, [37][38]. However, these approaches have limited expressivity. For example, [37] focus on finding subsumption relations between concepts of fuzzy ontologies, while our fuzzy semantic mapping framework provides 9 possible mapping relations. [38] do not address the comparison of fuzzy continuous ranges of values for properties, while in this paper we integrate measures for both discrete and continuous properties.

In this paper, we assume that the metadata on sensors is formalized in an ontological format. An ontology is usually defined as a set of concepts (or classes) that represent entities of the domain of discourse, relations and/or properties, and axioms, which are statements that are true within that domain of discourse [39]. We follow a similar approach to define the fuzzy geospatial ontology. However, in the fuzzy ontology, we consider that the membership degree of a property or relation in the definition of a concept can be quantified. In a crisp ontology, the membership degree of a property or relation into the definition of a concept is always one or zero. This means that either a concept has that property; or it does not have it. In the fuzzy ontology, this membership degree varies between zero and one, to indicate partial membership. Therefore, in a fuzzy ontology, concepts do not have a crisp definition.

We define the fuzzy geospatial ontology as a 5-tuple: $O = \{C, R, P, D, rel, prop\}$, where:

- C is a set of concepts, which are abstractions of entities of the domain of discourse;
- R is a set of relations;
- P is a set of properties for concepts;
- D is a set of possible values for properties in P, called range of properties;
- rel: $[R \rightarrow C \times C] \rightarrow [0, 1]$ is a fuzzy function that specifies the fuzzy relation that holds between two concepts;
- $prop$: $[P \rightarrow C \times D] \rightarrow [0, 1]$ is a fuzzy function that specifies the fuzzy relation between a concept and a subset of D. D is therefore a fuzzy range of values.

The set of relations R includes spatial relations such as "Is_located_at," which indicates the location of an instance of the concept, and other topological, directional and orientation spatial relations, which can be fuzzy. Therefore, in this paper we assume that either the query can contain a fuzzy property (e.g., "find sensors monitoring temperature close to point A," with point A being defined with a fuzzy function such as in Figure 4), or the sensor itself can be defined by a fuzzy property (its position in space being fuzzy), or both. The fuzzy semantic mapping mechanism takes into account these three cases, since fuzzy sets theory also include the case of crisp sets (where membership degree can only be 1 or 0).

For the purpose of our approach, we define a concept with a conjunction of a set of axioms A_C, where each axiom is a fuzzy relation or property that defines the concept:

$$C = A1 \sqcap A2 \sqcap \ldots \sqcap An.$$

We use the term axiom, which is usually employed to refer to the whole expression that defines a concept, because a concept could also be defined by one feature (property or relation).

The idea of the fuzzy semantic mapping mechanism is to use fuzzy logics to first determine the fuzzy inclusion of a concept into another concept from a different ontology (or, in the case of fuzzy propagation, the fuzzy inclusion of the query concept into another concept describing the semantics of sensor data), based on the fuzzy inclusion of each axiom of the first concept into axioms of the second concept. Then, fuzzy predicates, which value depends on the fuzzy inclusion, are used to infer the semantic relation between the two concepts.

Let two concepts C and C' be defined as follows:

$$C = A_1 \sqcap A_2 \sqcap \ldots \sqcap A_n$$

$$C' = A_1' \sqcap A_2' \sqcap \ldots \sqcap A_m'.$$

We define the fuzzy semantic mapping between C and C' as follows:

Definition (fuzzy semantic mapping) A fuzzy semantic mapping m^C between C and C' is a tuple $m^C = \langle C, C', rel(C, C'), \mu(C, C')\rangle$, where rel is a semantic relation between C and C', and $\mu(C, C')$ is the fuzzy inclusion of C into C'.

We define the fuzzy inclusion as the membership degree of a concept in another. This means that when the value of the fuzzy inclusion is 1, the first concept is entirely included in the second concept; when it is zero, no axiom of the first concept intersects with axioms of the second. The fuzzy inclusion of C into C' is denoted with $\mu(C, C')$:

$$\mu(C, C') = \frac{\sum_{A \in (A_1, \ldots, A_n, A_1', \ldots A_m')} \min(\mu_C(A), \mu_{C'}(A))}{\sum_{A \in (A_1, \ldots, A_n, A_1', \ldots A_m')} \mu_C(A)}, \qquad (1)$$

where $\mu_C(A)$ is the membership degree of axiom A in concept C. We know that this membership degree comes from the definition of the concept in the fuzzy geospatial ontology. Now there are two cases to consider: either the axioms are formed with properties with discrete range of values, or axioms are formed with properties with continuous range of values (i.e., a fuzzy function such as in Figure 4). In each case, the fuzzy inclusion must be computed using different formulas.

First, we explain how the fuzzy inclusion of C into C' defined in (1) is computed in the case of properties with discrete or continuous range of values. Secondly, we explain how the semantic relation rel between C and C' is determined using the fuzzy inclusion value.

A. *Fuzzy Inclusion: The Discrete Case*

Let A: $\langle r.D\rangle$ and A': $\langle r'.D'\rangle$ be two axioms, where D and D' are discrete fuzzy ranges of values (e.g., temperature = low, average, or high). For example, <temperature.((0.2, low);(0.8, average))> represents the partial membership of temperature value into the set of low and average temperature intervals.

To compute (1), which relies on the membership of axiom A in concept C', and where axiom A of concept C might not be already in the definition of the concept C', we need the membership of axiom A in axiom A' of C'. The membership degree of A into A' is determined by the Zadeh conjunction for fuzzy sets:

$$\mu(A, A') = \min(\mu(D, D'), \mu(r, r')) . \qquad (2)$$

Generally, the function $\mu(X1, X2)$ over any fuzzy sets $X1$, $X2$ is defined as follows, using the fuzzy implication principle of fuzzy logics [33]:

$$\mu(X1, X2) = \inf_{x \in X1 \cup X2}(\mu_{X1}(x) \Rightarrow_f \mu_{X2}(x)), \qquad (3)$$

where $\Rightarrow_f$ is a fuzzy implication operator from [0,1] into [0,1], and *x* is any element belonging to *X1* and/or *X2*. There are several definitions for the fuzzy implication operator (including Gödel, Gogen and Lukasiewicz fuzzy implications, see [33]). We use Lukasiewicz fuzzy implication because of its superior flexibility, which is defined as follow:

$$\mu_{X1}(x) \Rightarrow_L \mu_{X2}(x) = \begin{cases} 1 & \text{if } \mu_{X1}(x) \le \mu_{X2}(x) \\ 1 - \mu_{X1}(x) + \mu_{X2}(x) & \text{otherwise} \end{cases}. \qquad (4)$$

Now, we need to adapt formulas (3) and (4) to compute $\mu(D, D')$ and $\mu(r, r')$. For example, consider the problem of computing $\mu(D, D')$. Consider also that c_i' is an element of the fuzzy set *D*'. We see from (4) that we need to know the membership degree of elements of *D*' into *D* ($\mu_D(c_i')$), and vice-versa. However, this membership degree is not readily available, because elements of *D*' are not necessarily included in *D*. In other words, all we have is the membership degree of an element into the set to which it initially belongs. Nevertheless, it is possible to compute $\mu_D(c_i')$ if we know the membership degree of c_i' into elements of *D* (denoted with c_j). To do so, we use the Lukasiewicz fuzzy composition operator, denoted with the symbol $\otimes_L$, and which determines the membership of a first element c_i' in a set *D*, knowing the membership degree of c_i' in c_j and the membership degree of c_j in *D* (Figure 3). The symbol *c* is used to indicate an element of the range of values of a property or a relation of the fuzzy geospatial ontology.

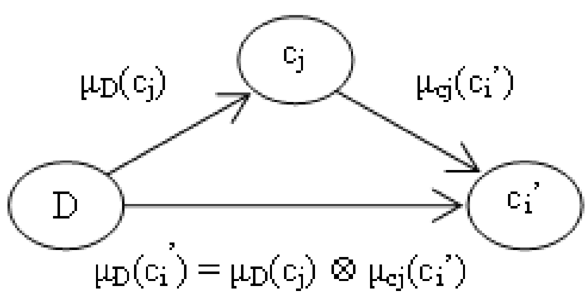


Figure 3. Illustration of the Lukasiewicz fuzzy composition principle

According to this principle, the membership degree of c_i' in *D* writes as:

$$\mu_D(c_i') = \sum_j \mu_D(c_j) \otimes_L \mu_{c_j}(c_i'), \ \forall j \left| (\neg c_j \perp c_i) \right., \qquad (5)$$

where

$$\mu_D(c_j) \otimes_L \mu_{c_j}(c_i') = \max(\mu_D(c_j) + \mu_{c_j}(c_i') - 1, 0), \qquad (6)$$

according to Lukasiewicz's definition of the fuzzy composition operator.

To determine $\mu_{cj}(c_i')$, which is the membership degree of an element c_i' of a range of values in an element c_j of another range of values, we have developed a fuzzy membership degree measure. This measure is based on the relative position of c_j and c_i' in an upper-level ontology *O*. An appropriate ontology for this task is a domain-independent, largely recognized lexical base, such as WordNet. However, other specialized upper-level ontologies might be more useful, depending on the domain of application. Of note however is that the chosen upper-level ontology should be structured with is-a relations. This is because is-a relations allow to identify inclusion relations between elements of the ontology, which allows to derive membership degrees. We note that using such external resource allows to deal with the terminological heterogeneity that characterizes the metadata of sensors produced by different organizations. Let $<_O$ be a hierarchical, is-a relation between terms *t* in *O*, such that $t <_O t'$ means that *t* is more specific (less general) than *t*'. Let $P(c_j, c_i')$ be the path relating c_j to c_i' in *O*, according to this hierarchy: $P(c_j, c_i') = \{c_j, t1, t2, \ldots c_i'\}$ so that *t*1, *t2*, … is the ordered set of nodes (representing terms) from c_j to c_i' in *O*. Let $d(t_k)$ be the set of descendants of a node t_k in *O*. We define $\mu_{cj}(c_i')$ as follows:

$$\mu_{c_j}(c_i') = \begin{cases} 1 & \text{if } c_i' \prec c_j \\ \dfrac{1}{\prod_{\forall t_k \in P(c_j, c_i')} \left| d(t_k) \right|} & \text{if } c_i' \succ c_j \\ 0 & \text{otherwise} \end{cases}. \qquad (7)$$

This equation means that when c_i' is more specific than c_j, it is entirely included in c_j, and when c_i' is more general than c_j, $\mu_{cj}(c_i')$ decreases with the number of descendants of its subsumers. Replacing results of (7) in (6), we obtain the membership of each element of the fuzzy range *D*' in *D*, which, in turn, allows to determine $\mu(D, D')$ with (3). Equation (7) is also used to determine $\mu(r, r')$, so these results can be replaced in (3).

The fuzzy inclusion values between the axiom also allows to determine the semantic relation between these axioms. From the fuzzy inclusion given in (2), we obtain the semantic relation between the axioms, *rel*(*A*, *A*'), using the following rules, which are derived from the fuzzy set relationship definitions:

(R1) $A \equiv A' \Leftrightarrow \mu(A, A') = 1 \wedge \mu(A', A) = 1$

(R2) $A \sqsubseteq A' \Leftrightarrow \mu(A, A') = 1 \wedge \mu(A', A) < 1$

(R3) $A \sqsupseteq A' \Leftrightarrow \mu(A, A') < 1 \wedge \mu(A', A) = 1$

(R4) $A \sqcap A' \Leftrightarrow 0 < \mu(A, A') < 1 \wedge 0 < \mu(A', A) < 1$

(R5) $A \perp A' \Leftrightarrow \mu(A, A') = 0 \wedge \mu(A', A) = 0$.

Semantic relations between the axioms will enable to determine the semantic relation between the concepts that they compose. Before we show how this can be done (in Section C), we present the case of fuzzy inclusion between properties with continuous ranges of values.

B. Fuzzy Inclusion: The Continuous Case

Properties can have continuous fuzzy ranges of value described by fuzzy membership functions. Their general form is *A*: <*p*.*f*> and *A*': <*p*'.*f*'>, where *p* and *p*' are properties and *f* and *f*' are fuzzy continuous functions. For example, Figure 4 shows the comparison of two fuzzy membership functions describing fuzzy spatial regions *sr*' and *sr*' (e.g., fuzzy spatial location targeted by the query and fuzzy spatial area of measurement of the sensor). Such function represents the uncertainty bounds for a class of fuzzy spatial regions.

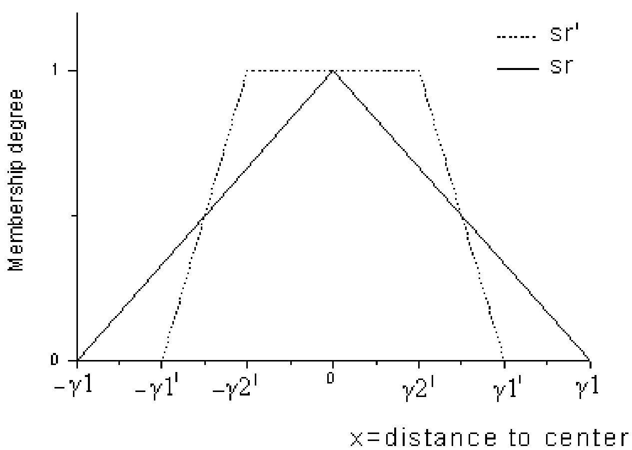


Figure 4. Example of fuzzy functions for defining a fuzzy point (geographical location)

The choice of the fuzzy function to represent the range of a property depends on the characteristics specific to the sensor, especially how the accuracy of the measurement changes in space. For example, in Figure 4, *sr* is a triangular fuzzy function; the membership degree of a point in space into the sensor's area of measurement is maximal only at a single, punctual location (*x*=0). As the distance to this single location increases, the membership degree decreases linearly and symmetrically. Such fuzzy function can be suitable to represent the area of measurement of a sensor that monitors the temperature at a certain fuzzy point, for example. Meanwhile, *sr*' represents a fuzzy trapezoidal function where the membership degree of a point in space into the sensor's area of measurement is maximal inside a given radius. Outside this radius, the membership degree decreases linearly (and more sharply than in the given triangular function). Such fuzzy function may be more suitable to describe a sensor that can detect movement within a given circular area, for example. We can also see that the slope depends on how precise the measurement is in space and therefore depends on the sensor's characteristics. Other common fuzzy functions are presented in [40].

The membership degree *A* into *A*' is computed with (2), except that the membership of *f* into *f*' is not computed with (3), which is applicable only to discrete fuzzy sets. Instead, we need to study inclusion measures for continuous fuzzy sets. A review of similarity and inclusion measures for fuzzy sets is presented in [41]. Notably, the measure for erosion of fuzzy sets by [42] is presented as a suitable measure to measure fuzzy inclusion for finite sets. Since no measurement domain of sensors can be infinite, a fuzzy inclusion for finite sets is appropriate. According to this measure, the membership of *f* into *f*' can be computed with the following function:

$$\mu(f, f') = \int_0^1 \inf_{x \in f^\alpha} \mu_{f'}(x) d\alpha , \tag{8}$$

where *x* is an element of the universe of discourse (or of the union of the domains of *f* and *f*'), and f^α is called the α-cut of f, which is the binary set with defined as follows:

$$f^\alpha(x) = \begin{cases} 0 \text{ if } \mu_f(x) \prec \alpha \\ 1 \text{ if } \mu_f(x) \geq \alpha \end{cases} \tag{9}$$

Note that this approach is used not only for spatial or temporal properties, but also for the case of thematic property axioms with fuzzy continuous ranges of value, for example A: <HasWindSpeed.Low>, where low is a continuous fuzzy range of values over the values of wind speed.

C. Semantic Relations

In order to determine the semantic relation between the query concept and a concept describing semantics of sensor data, we have defined a set of three predicates. Predicates are measurements which values are qualitative; they are used to determine whether a semantic relation between two concepts is true. The semantic relations between two concepts are qualitative relations among the following: equivalence, contains, contained in, partial symmetric-containment, partial left-containment, partial-right containment, strong overlap, weak overlap, and disjoint (as listed in Table 1). The semantic relation is determined by the following expression:

$$rel(C, C') = \\ I(A_C, A_{C'}) \otimes_{\Pr} C(A_C, A_{C'}) \otimes_{\Pr} CI(A_C, A_{C'}), \tag{10}$$

where $I(A_C, A_{C'})$, $C(A_C, A_{C'})$ and $CI(A_C, A_{C'})$ are three predicates that respectively evaluate the following:

- $I(A_C, A_{C'})$ predicate evaluates the intersection of axioms of the concept C with axioms of C';
- $C(A_C, A_{C'})$ predicate evaluates the inclusion of axioms of C' in axioms of C, and
- $CI(A_C, A_{C'})$ predicate evaluates the inclusion of axioms of C in axioms of C'.

The $\otimes_{Pr}$ symbol in (10) is a composition operator. Its function is to give the semantic relation between C and C', based on the value of the three predicates.

For any predicate Pr, the possible values of Pr are:

- B value, if for all axioms of C there is an axiom of C' that verifies predicate Pr, and vice-versa. For example, $I(A_C, A_{C'}) = B$ if for all axioms in A_C, there is an axiom in $A_{C'}$ that intersects this axiom (as determined by rules R1 to R5 defined in the previous section), and vice-versa;
- S value, if there exist some axioms of C and axioms of C' that verify predicate Pr, but not all;
- N value, if there exists no axiom of C and C' that verifies predicate Pr.

These principles for determining the value of a predicate are formally expressed as follows (where logic symbols are $\forall$ (for all), $\exists$ (there exists) $\perp$ (disjoint) and $\neg$ (negation)):

$$I(C,C') = \begin{cases} B & \forall i \exists j, rel(A_i, A'_j) \neq \perp \wedge \mu(A_i, A'_j) \neq 0) \wedge \\ & \exists i \forall j, rel(A_i, A'_j) \neq \perp \wedge \mu(A_i, A'_j) \neq 0) \\ S & \exists i \exists j, rel(A_i, A'_j) \neq \perp \wedge \mu(A_i, A'_j) \neq 0) \wedge \\ & \neg[\forall i \exists j, rel(A_i, A'_j) \neq \perp \wedge \mu(A_i, A'_j) \neq 0) \wedge \\ & \exists i \forall j, rel(A_i, A'_j) \neq \perp \wedge \mu(A_i, A'_j) \neq 0)] \\ N & \neg \exists i \exists j, rel(A_i, A'_j) \neq \perp \wedge \mu(A_i, A'_j) \neq 0) \end{cases}$$

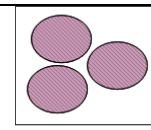
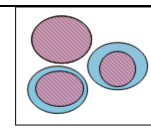
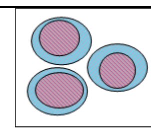
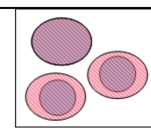
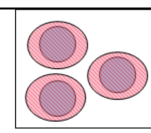
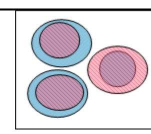
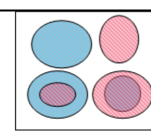
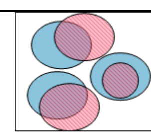
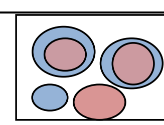
$$C(C,C') = \begin{cases} B & \forall i \exists j, rel(A_i, A_j') \in \{\equiv, \supseteq\} \wedge \mu(A_i, A_j') \neq 0 \\ S & \exists i \exists j, rel(A_i, A_j') \in \{\equiv, \supseteq\} \wedge \mu(A_i, A_j') \neq 0 \wedge \\ & \neg \forall i \exists j, rel(A_i, A_j') \in \{\equiv, \supseteq\} \wedge \mu(A_i, A_j') \neq 0 \\ N & \neg \exists i \exists j, rel(A_i, A_j') \in \{\equiv, \supseteq\} \wedge \mu(A_i, A_j') \neq 0 \end{cases}$$

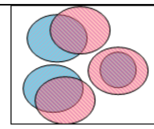
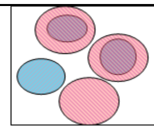
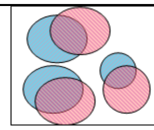
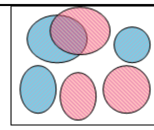
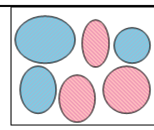
$$CI(C,C') = \begin{cases} B & \forall i \exists j, rel(A_i, A_j') \in \{\equiv, \subseteq\} \wedge \mu(A_i, A_j') \neq 0 \\ S & \exists i \exists j, rel(A_i, A_j') \in \{\equiv, \subseteq\} \wedge \mu(A_i, A_j') \neq 0 \wedge \\ & \neg \forall i \exists j, rel(A_i, A_j') \in \{\equiv, \subseteq\} \wedge \mu(A_i, A_j') \neq 0 \\ N & \neg \exists i \exists j, rel(A_i, A_j') \in \{\equiv, \subseteq\} \wedge \mu(A_i, A_j') \neq 0 \end{cases}$$

For C and C', the domain of quantifiers i and j is respectively $i \in \{1,\ldots, n\}$ and $j \in \{1,\ldots, m\}$.

As for the composition operator $\otimes_{Pr}$, it takes as input the value for the three predicates for C and C', and returns the semantic relation between C and C', according to the 14 possible combinations of predicate values identified in Table 1. This table defines the $\otimes_{Pr}$ operator: each combination of values for the three predicates is associated with a resulting semantic relation. For example, C (semantically) contains C' if $I(A_C, A_{C'}) = B$, $C(A_C, A_{C'}) = B$ and $CI(A_C, A_{C'}) = S$ (second line of Table 1). In the associated illustrations, blue sets represent axioms of C, and red sets axioms of C'.

TABLE I. SEMANTIC RELATIONS IN FUNCTION OF THE COMBINATION OF PREDICATE VALUES ($\otimes_{Pr}$ OPERATOR)

Semantic relationship (C, C')	Value of $I(A_C, A_{C'})$	Value of $C(A_C, A_{C'})$	Value of $CI(A_C, A_{C'})$	Representation
1. Equivalence	B	B	B	
2. Contains	B	B	S	
	B	B	N	
3. Contained In	B	S	B	
	B	N	B	
4. Partial S-Containment (S=Symetric)	B	S	S	
	S	S	S	
5. Partial L-Containment (L-LEFT)	B	S	N	
	S	S	N	

6. Partial R-containment (R=RIGHT)	B	N	S	
	S	N	S	
7. Strong Overlap	B	N	N	
8. Weak Overlap	S	N	N	
9. Disjoint	N	N	N	

This fuzzy semantic mapping mechanism describes how the fuzzy inclusion and semantic relation can be computed between a query concept and semantics of sensor data, and therefore supports fuzzy query propagation. It is worth noting that the approach requires the user to formulate within its query a fuzzy function for the fuzzy properties, which might not be straightforward for users who are not familiar with fuzzy set theory. Therefore, we note that further work is required to develop a friendly interface to help capture the fuzziness in user's queries in an easier fashion. Similarly, the approach requires that the fuzziness of sensor data be formally described and available within sensor metadata. In this respect, we note that several proposals have already been made for the development of Fuzzy Description Logics (DL) [40], DL being the underlying formalism of OWL, the W3C-recommended language for the Semantic Web [43].

VI. Evaluation

In this section, we present the evaluation of the fuzzy query propagation approach. The presented evaluation is based on the comparison of the approach with the flooding algorithm, which consists in flooding the network through all available communication channels between sensors. We also compare the crisp version of the algorithm with the fuzzy version to verify whether the fuzzy algorithm helps to find more relevant sensors than the crisp version. Finally, to further investigate the behavior of the algorithm, we compare the results using different fuzzy inclusion thresholds as criteria to select query recipient nodes.

The approach was implemented as a simulation in Java (Eclipse 3.4, JDK 1.6) with a maximum of 20,000 nodes. Nodes were randomly assigned metadata using a set of metadata into which variations were randomly introduced. The original metadata was obtained from the SensorML descriptions available on the Geospatial Cyberinfrastructure for Environmental Sensing platform (GeoCENS), an online platform that enables simplified searching, storing and sharing of environmental and other georeferenced data [2], to which we have added fuzzy membership functions on their location and some thematic attributes (e.g., temperature, precipitations and soil moisture) for the purpose of the simulation.

The simulations performed were compared in terms of the rate of dissemination of the query to the relevant sensor nodes. The approach is efficient if the least sensor nodes are sent messages for a maximum of relevant nodes being reached and identified as query recipients. The rate of dissemination compares the percentage of relevant nodes that were selected as query recipients (vertical axis) versus the number of sensor nodes that were reached (i.e., that received the query message) (horizontal axis). Therefore, we are not only evaluating the ability of the algorithm to propagate the query while reducing energy consumption, but also the ability to find the best path to maximize the recall and accuracy. The relevant nodes with respect to a query were identified manually during the setting of the simulation and used as authoritative result for the evaluation of the approach.

Figure 5 shows the assessment of the rate of dissemination for the flooding, crisp, and fuzzy algorithms, tested with a fuzzy inclusion threshold of 0,40.

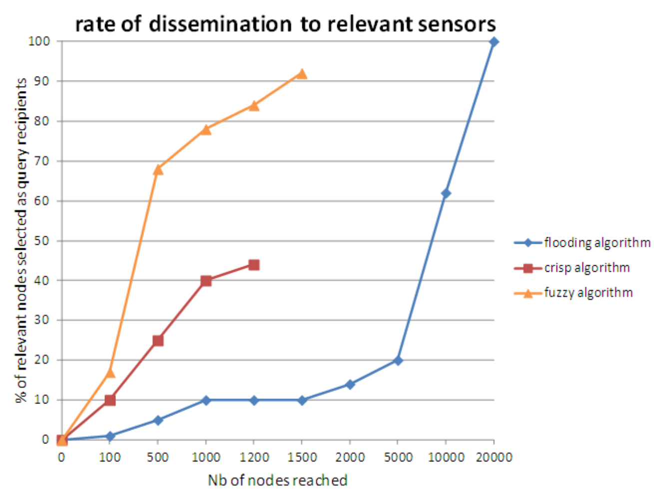


Figure 5. Rate of dissemination using flooding, crisp or fuzzy propagation algorithm

The flooding algorithm, because it reaches all nodes of the network, is able to achieve a 100 percent recall of relevant sensor nodes. But this is only at the very high cost of sending messages to all nodes of the network, which is not appropriate in an environment where the energy of sensors must be saved since it is not guaranteed that sensors are easily accessible and can be replaced or their energy source renewed; for example some sensors are buried to measure soil moisture, while others are underwater to measure water temperature, etc. Meanwhile, the crisp algorithm can only achieve a 43 percent recall of relevant nodes. This is because the crisp query is very restrictive in comparison with the fuzzy query. While the fuzzy algorithm is more costly that the crisp algorithm (20 percent more nodes received a query message), its performance counterbalances this cost since the recall of relevant nodes reaches over 90 percent.

Figure 6 shows the rates of query dissemination to relevant sensors for different values of the fuzzy inclusion threshold (0,20, 0,40, 0,60 and 0,80).

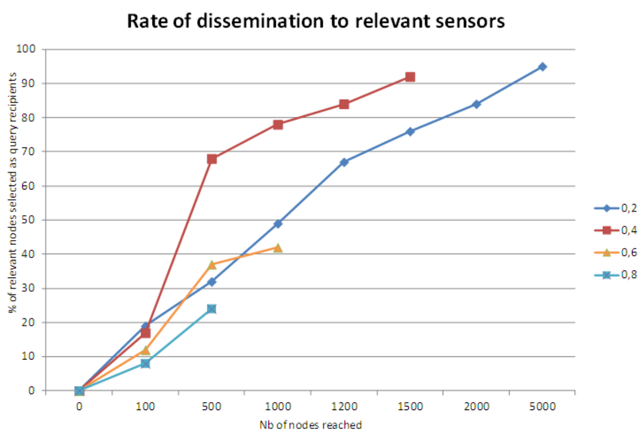


Figure 6. Rate of dissemination using various fuzzy inclusion thresholds

When the algorithm is set with a 0,20 or 0,40 fuzzy inclusion threshold, the difference in the recall of relevant nodes is very slight, suggesting that even low fuzzy inclusion between 0,20 and 0,40 might be sufficient to indicate relevance.

However, with a low threshold, a significant number of sensor nodes that are not relevant are accessed in comparison with the 0,40 threshold. With the 0,60 and 0,80 thresholds, an important percentage of relevant nodes are missed and the query propagation is stopped after reaching a smaller number of nodes. Although this study does not demonstrate which threshold is appropriate at all times, since this is likely to depend on the data being used, this demonstrates that the choice of the fuzzy inclusion threshold is a determining factor influencing the efficiency of the approach. Therefore, a testing phase with sample network is necessary to establish the more relevant threshold.

VII. Conclusion and Future Work

In the geospatial domain, it is essential to consider the uncertainty and fuzziness of geospatial phenomena. In a previous paper, we had presented an approach for fuzzy semantic mapping of fuzzy geospatial ontologies [6]. In this paper, we have demonstrated one of the possible applications of this approach through incorporating it into a new approach for fuzzy query propagation in sensor networks.

Sensors are devices intended to monitor environmental conditions, and they can be interconnected through so-called sensor networks. Due to energy, processing and memory limitations pertaining to their size, sensors of a network cannot be all reached by an application. They must rather be queried and their data retrieved through intermediary sensor nodes of the network. This situation creates the need for query propagation mechanisms that are efficient in terms of cost, but that are also able to retrieve requested data. At the same time, we believe that the fuzziness of query and sensor data must be taken into account in query propagation to improve the ability to retrieve relevant data. This created the motivation for the fuzzy query propagation approach that has been proposed in this paper. The fuzzy query propagation approach comprises a first propagation step towards relevant clusters of sensors, therefore varying the sensor nodes that will have to redistribute the query; it is followed by an intra-cluster query propagation phase. In both phases, the fuzzy semantic mapping mechanism is used to select query recipients. The experiments that were conducted show that in comparison with a crisp approach, taking into account the fuzziness indeed improves the recall of relevant data while avoiding the increase of propagation cost. We have also noted that one challenge or limitation raised by our research is related to the impact on the performance of the approach of some parameters of the proposed algorithm, including the fuzziness threshold being chosen to select query recipients. Therefore, further research is required to investigate avenues for helping the user to select the appropriate threshold in a user-friendly fashion.

Among future work being uncovered by this study, we plan to investigate the role of such fuzzy query propagation approach into the so-called semantic enablement of Spatial Data Infrastructures (SDIs). Because the objective of SDIs is to support the exchange of heterogeneous data and information among various providers and users, future research on SDIs will aim at integrating access to sensor networks through SDIs. Therefore, we foresee that future work on how to integrate fuzzy query propagation as a service into SDIs will be useful. Semantic-based query propagation strategies such as provided in this paper can be adapted to SDIs and coordinated with catalogue services so that the user can, through a single interface, search for either data from web services registered in centralized catalogues or data from dynamic networks made accessible through SDIs.

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