Tracking topological relationships and spatiotemporal changes occurring in vague shape phenomena monitored by sensor network: a distributed fuzzy reasoning approach

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Abstract

Sensor data are increasingly used to monitor and observe spatiotemporal phenomena in a wide range of applications, such as flood management, urban traffic, air quality control, and forest fire management. Real-time modeling and representation of these evolving phenomena are fundamental for efficient and timely decision-making processes. In the context of multisensory systems, where two phenomena (e.g., air pollution index and wind conditions) can be sensed simultaneously by networked sensors, analyzing the relationships between them is a key issue for decision-making. Understanding whether the extent of pollution is expanding or contracting around a specific location, or whether it coincides with a windy zone, can support the adoption of more effective strategies. A sensing system equipped with a rule-based reasoning engine, capable of inferring spatiotemporal changes and the topological relationships between sensed phenomena with broad boundaries over time, provides decision-makers with precise and unambiguous information. In this paper, spatial changes and topological relationships for fuzzy-crisp objects representing phenomena with vague boundaries are conceptualized using an Extended Fuzzy Spatiotemporal Change Pattern (FESTCP) and a 5×5 Intersection Model (I5x5M), respectively. The rule-based reasoning engine proposed here is based on this conceptualization. To evaluate the method, a simulated case study of air pollution in Quebec City was conducted. The results demonstrate that the proposed approach effectively captures the spatiotemporal evolution of an air pollution episode, providing valuable information for real-time decision-making in real-world applications.

1. Introduction

Sensor data streams are a fundamentally novel mechanism to deliver observations data about monitored phenomena to information and decision systems (Whittier et al., 2017). According to Bill et al.(2022), developments in the area of sensor networks during the last decade put us on the way towards realizing the vision of «world of real-time geographic information» promoted by (Goodchild, 2009). In such a vision as for many application fields, decision making process is supported by geospatial information derived on a real time basis. Since sensors are limited in observation range, bandwidth, memory, battery life, and computation power (Idrees & Al-Qurabat, 2021), computing spatial information related to large spatial phenomena requires sensor network (SN) which cover the spatial extent of the phenomena of interest. According to Ntankouo Njila et al. (2021b), many of such observed phenomena as forest fire, air pollution, traffic noise etc., are characterized by undefined and vague geometry. Even though sensors can be considered as location-aware data recorder (Zhou et al., 2024), a sensor cannot provide alone, spatiotemporal information about the phenomenon of wide spatial extent, these sensors require collaborations among neighboring nodes to compute such spatial information.

n such a decentralized spatial computing approach, sensor positions will generally not align exactly with the edges of the phenomena, whose spatial boundaries are inherently vague. On the other hand, sensor density, which varies across the network, is a key factor in ensuring the quality of the derived spatial knowledge regarding the extent, geometry, and dynamics of the monitored phenomena (Whittier et al., 2017). These lead to some uncertainties in derived spatial knowledge while computing the geometry of monitored phenomenon from sensor records (Bleisch et al., 2012). Existing decentralized spatial computing approaches for reasoning about and modeling sensed phenomena often assume that these phenomena can be represented as spatial objects with crisp boundaries. However, this assumption does not reflect the real-world nature of many environmental phenomena, whose boundaries are inherently fuzzy (Schneider, 2008).

For in situ sensing, sensor data value stands as proxy of the manifestation of occurring real world phenomena (Yu et al., 2020); in addition to the sensors location and the spatial range of sensors observations, these data values represent the spatial signature of monitored phenomenon. It is from these distributed and localised signatures over time that spatial reasoning can be carry out by sensor systems to infer on topological relationships that hold between sensed phenomena in multisensory systems, and ongoing changes in dynamic phenomena. Sensors are in this context changed into ambient intelligent agents that collaborate among them for the benefit of end users at a higher spatial level than on the basis of raw data (Gams et al., 2019). These ambient agents should be equipped with rule-based reasoning engine from which sensor data are directly changed into discrete spatial information. The reasoning rules are established based on built knowledgebase describing how such vague shape phenomena are modeled and how the spatial relationships and changes are conceptualized. We adopt fuzzy-crisp spatial object made of a core (Kernel) and a conjecture (broad boundary) part (Pauly & Schneider, 2010), as the best object-based conceptualization of vague shape phenomena.

This paper proposes a decentralized fuzzy reasoning approach in which sensors collaborate to compute their spatial statuses over time based on the information conveyed by the collected data. Both sensor and sink nodes in this approach are equipped with built-in inference engines to deduce the geometry of the monitored phenomena, their topological relationships, and spatiotemporal changes. The inference rules used to determine

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the topological relationships among fuzzy sensed phenomena are established based on the underlying structure of a 5x5 Intersection Matrix ($I_{5x5}M$). Also, we extended the change pattern proposed by Yang et al. (2008) into a Fuzzy Extended Spatiotemporal Change Pattern (FESTCP) to model spatial changes about vague shape phenomena and formulate the predicates of our event-calculus reasoning approach used to infer spatiotemporal changes from sensor data.

The remainder of the paper is organized as follows. Section 2 presents the methodology and principles used to extract the geometry of monitored phenomena based on a fuzzy-crisp object model, as well as to analyze topological relationships and spatiotemporal changes. Section 3 presents a simulated case study of urban air pollution under windy conditions, monitored by a sensor network and implemented in NetLogo (Wilensky & Rand, 2015), to evaluate the performance of the proposed approach and its applicability to real-world phenomena. The final section concludes this paper.

2. Methodology

Object-oriented GIS is adopted in many applications where real-world and its constituent elements and features are seen as objects and changes as events. This is because this approach is intuitive to human thinking and spatial cognition (Shaw & Sui, 2020). For large area continuous dynamic phenomena, static sensing agents composing the SN, due to their limited sensing range, will deliver data about limited spatial extent. From these data, sensor nodes can only infer local spatial information about their relative position in respect to the extent of monitored phenomenon at a given time (Ntankouo Njila et al., 2021b). These relative spatial and temporal information locally computed by sensors are consistent facts used in inferring topological space defining the geometry of monitored phenomena from which spatial relations and changes are inferred. This should be done considering the fuzzy nature of sensed phenomena.

2.1 Computing spatiotemporal status of sensors from sensor data

The proposed spatial reasoning approach used sensor data values to infer on the relative position of a sensor in respect to the spatial extent of monitored phenomena. This relative position is based on the fuzzy-crisp object model made of a core (Kernel) and a conjecture (broad boundary) part, used as the conceptual representation of vague shape phenomena. To evaluate the relative position of sensors towards the spatial extent of monitored phenomena, a membership function which is defined according to the nature of monitored phenomena and physical laws that define its properties is used. The relative position of each sensor defines its spatial status at a given time. This spatial status defines if the location of each node belongs to the inner part (kernel or conjecture) of its spatial extent or its outer part.

This is set as follows:

$$f(Sr): Sr \rightarrow [0,1] \tag{1}$$

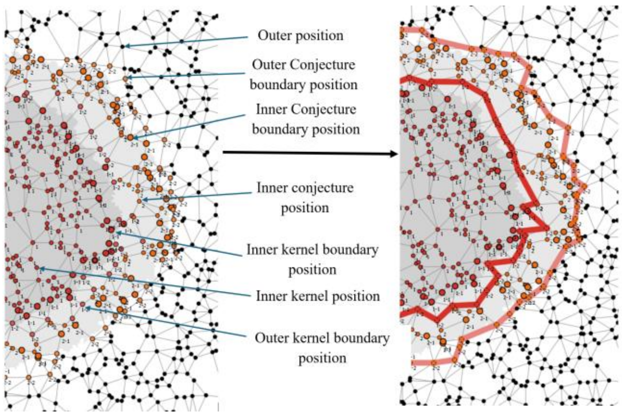
Where $\boldsymbol{f}$ is a membership function and $\boldsymbol{Sr}$ is a sensor record value.

If $\boldsymbol{\mu}$ is the membership value of a sensor record at a given time $\boldsymbol{t}$, The relative position of each sensor node noted as *Loc(S)* is deduced from logic rules as follows. Let’s consider a threshold value $\boldsymbol{\alpha}$ defined in accordance with phenomena semantics, where $0 < \alpha < 1$

$$\begin{gathered} If\ \mu \geq \propto then\ Loc(S) \in Kernel \\ If\ 0 < \mu < \propto then\ Loc(S) \in Conjecture \\ If\ \mu = \ 0\ then\ Loc(S) \in Outside \end{gathered} \tag{2}$$

Considering the geometrical space which define the extent of monitored phenomena as a set of spatial positions made of sensor locations as suggested by Mocnik (2022), it is necessary to identify the topological parts that build the spatial extent of monitored phenomena. These topological parts are delignated by polygons made of vertices and line. Sensor nodes won’t be able from their single observations to know if they are close of far of these boundaries, they need to collaborate with their direct linked nodes (one-hop). Because sensor positions will rarely match the boundaries of such continuous phenomena, vertices identification should follow more appropriate rules.

In this collaboration, only sensors detecting the kernel or conjecture parts defining the geometry of monitored phenomenon, set and send queries to their one-hop neighbor nodes to infer on if their positions are close to the boundary of the kernel or conjecture part. Form this collaboration, each node is able to state on it’s spatial status based on the type of queries and answers received from it’s neighboring nodes. Seven sets of sensors spatial statues are identified and used to build the geometry of the fuzzy-crisp object representing the phenomenon extent at a given time as shown in figure 1.



a) b)

Figure 1. Excerpt of SN showing: a) the seven spatial statues of sensor nodes, b) built boundaries of the kernel (gray) and conjecture (light gray) parts of monitored phenomenon at a given time.

The kernel and conjecture vertices used in building the limits that make the geometry of fuzzy-crisp object representing the spatial extend of monitored phenomenon at a given time, are identified using 3 approximation approaches: Maximalist, Minimalist and weighted according to the nature of monitored phenomenon. These approximation approaches are set by using the 2 sets (inner or outer) boundary position of nodes for the kernel or the conjecture part. In a maximalist approximation approach, the outer positions are considered as vertices while for minimalist approximation, the inner boundary positions constitute the vertices. For weighted approximation, vertices are set between these two sets (inner, outer) of boundary position along the communication link. In figure 1, the limits of the kernel and conjecture parts are drawn using a maximalist approximation.

2.2 Computing topological relationships from sensor network (SN) measurements

In multisensory systems, sensor nodes are equipped with different sensing units to observe and detect several phenomena at the same time. For a given multi-sensing system, if each sensing node can capture air pollution index and ongoing

temperature or wind speed, the pollution managing office would like to know if the pollution area is within the zone under heavy wind conditions to adopt a proper pollution fighting strategy. To do this, the two sensed phenomena are conceptually represented following fuzzy-crisp region model as formerly defined. The detection of each of monitored phenomenon is based on particular and well-defined membership functions.
The 5x5 intersection matrix (*$I_{5x5}M$*) which according to Ntankouo Njila et al (2021a) consistently consider the spatial structure of fuzzy-crisp object, is adopted to model spatial relationships. The topological relationship between 2 given phenomena A and B is logically traduced in a 5x5 intersection matrix (*$I_{5x5}M$*) defined as follows:

$$I_{5X5}(A,B) = \begin{bmatrix} A^1\cap B^1 & A^1\cap\partial B^1 & A^1\cap B^0 & A^1\cap\partial B^0 & A^1\cap B^- \\ \partial A^1\cap B^1 & \partial A^1\cap\partial B^1 & \partial A^1\cap B^0 & \partial A^1\cap\partial B^0 & \partial A^1\cap B^- \\ A^0\cap B^1 & A^0\cap\partial B^1 & A^0\cap B^0 & A^0\cap\partial B^0 & A^0\cap B^- \\ \partial A^0\cap B^1 & \partial A^0\cap\partial B^1 & \partial A^0\cap B^0 & \partial A^0\cap\partial B^0 & \partial A^0\cap B^- \\ A^-\cap B^1 & A^-\cap\partial B^1 & A^-\cap B^0 & A^-\cap\partial B^0 & A^-\cap B^- \end{bmatrix} \quad (3)$$

Where $A^1, \partial A^1, A^0, \partial A^0$ *and* A^{-1} correspond to the kernel, boundary of the kernel, conjecture, boundary of the conjecture and exterior of A, respectively, and $B^1, \partial B^1, B^0, \partial B^0$ *and* B^{-1} correspond to the kernel, boundary of the kernel, conjecture, boundary of the conjecture and exterior of B, respectively. This matrix is built through the aggregation of local spatial states of sensor nodes over the SN. Each local spatial status describing the coexistence of a topological part of A with another topological part of B. for illustrative purposes:

conjecture (A) ∩ Exterior (B) ≠ Ø means that this given sensor node is within the conjecture part of A and in the exterior part of B at a given time. The corresponding element in the matrice M will then hold a value of 1 for true; else the value is 0. The 25 elements of the matrice are binary components. The resulting *$I_{5x5}M$* which is compiled at the level of the sink node is used to infer on ongoing spatial relation that holds between A and B at a given time *t*. Inferring rules are established considering the structure of the 44 cases of spatial relations that may hold among fuzzy-crisp objects as presented by Clementini and Di Felice (1997).

2.3 Inferring spatial change over time in SN

In object-oriented GIS, objects in classes may change from one state to another, the changes themselves are not explicitly handled but are implicit in the variations in the properties of the objects (Worboys, 2001). An object θ changes if and only if there exists a property P of θ and distinct times t and t' such that θ has property P at t and θ does not have property P at t'. State returns the state of an object at a given time, that is, the values of its spatial and non-spatial properties at that time (Ferreira et al., 2014); similarly, sensor data describe monitored phenomena at a given time from which the spatial pattern of the very phenomenon is computed. Change in sensor data value over time expresses the dynamic character of monitored phenomena.
Event and process are essential constituents in geo-spatial dynamism which requires computation of both spatial and temporal characteristics (Jayanthi & Uma, 2019). Geo-spatial dynamism is essential for many applications in GIS as environmental resource planning, renewable resource management, disaster mitigation and environmental impact assessment etc. Changes in consecutive sensor data values is the main proxy for event and process describing the dynamism dimension of monitored phenomena.
Despite the granularity of sensor observations as compared to the extent of monitored phenomena of region nature and the vague shape and fuzzy nature of such phenomena, computing spatiotemporal information in such context, requires a more consistent knowledge-based approach for an efficient decision-making system. The computation approach suggested is based on the change of sensor spatial status from one to other of the 7 sets of spatial statuses formerly presented. For instance, from one date t_0 to the next t_1, if a sensor holding an inner or outer kernel boundary position at a given initial time t_0 which subsequently has a spatial status of inner conjecture type at t_1 this will definitely express the fact that: the monitored phenomenon continues to **hold** in its vicinity, but that a *decrease* in the phenomenon amplitude and a local *kernel shrinkage* is **happening** in its vicinity. What the decision maker would also like to know is whether the spatial extent of the phenomenon is *shrinking* or *expanding* or it is *moving* from one spot to another one, in other to adjust his intervention strategy.
Instead of being computed at a local level of sensor nodes, an integration of the whole set of local spatial events computed over the SN extent is required to compute such global spatiotemporal information. The reasoning rules used to infer on ongoing changes should be set based on special significance the patterns of changes detected. In order to consider the fuzzy nature of monitored phenomena, we proposed an extended version of the SpatioTemporal Change Pattern (STCP) suggested by Yang *et al.* (2008). The fuzzy extended spatiotemporal change pattern suggested is based on the fuzzy-crisp spatial region object model and shown in figure 2.

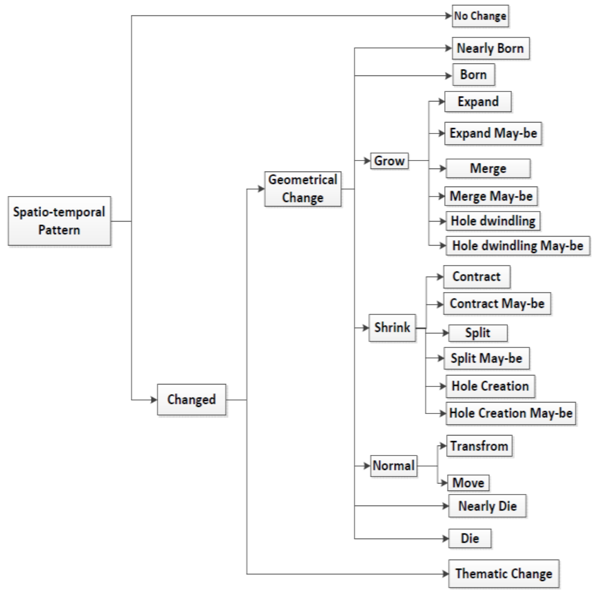


Figure 2. Fuzzy Extended Spatiotemporal Change Pattern (FESTCP)

In the proposed reasoning approach, the spatial status of each sensor node at time (*t*) is compared to its immediate parent status (status at *t_{-1}*) to infer on the spatial or thematic ongoing change. All local changes detected over the SN extent are aggregated at the level of the sink node and set in clusters. The reasoning rules are established in accordance with the nature of inferred changes and the geometry of each cluster. For instance, if the whole set of local change is made of two clusters: *kernel expand* and *conjecture expand*, then the spatial extent of the phenomenon is *expanding*. Instead, if the change cluster is essentially made of *conjecture expand* the resulting spatiotemporal change will be *Expand May-be*.

The built-in Event calculus Engine (ECE) which is part of the reasoning engine, uses a knowledge base and a rule-based component to infer on event detection and their spatial effect. The proposed approach is built on three steps computation based on deductive logic programming; following the principles of Event calculus (Mueller, 2008); these steps are:

- Reifying qualitative spatiotemporal status (fluent) from sensor data stream
- Identifying local spatiotemporal change based on consecutive spatial status
- Aggregating spatial changes inferred by sensor nodes and inferring developing spatiotemporal changes about monitored phenomenon

To cope with the limited storage and computing capacity of sensors, the current spatial status (at time t) of sensor nodes which is inferred from current measurement, is compared to its previous status (at time t-1) to trigger further computation and communication activities. If there is consistent change in data value which may lead in a change in its spatial status (for example, changing from *outer* to *conjecture status* or *kernel status*), the node will then initiate collaborations with link nodes for boundary detection; if not there will be no computation and no communication activity. The sensor status can therefore be inferred as one of the seven spatial statues. This change, which may lead to a modification in the spatial status of neighboring nodes, will induce the transmission of the current spatial status of each node to the sink node. When there is a difference between consecutive statuses, the previous state is replaced by the successor state in a small buffer storage unit within the sensor, and subsequently at the sink node, where aggregated sets of updated statuses are maintained. A simplified presentation of the proposed reasoning strategy and procedure is shown in Figure 3.
In this approach, if the spatial status of each sensor reflects a dual state with respect to two given phenomena, the inferred spatial information is based on the topological relationships between the monitored phenomena. The computation of ongoing changes in these topological relationships follows the same procedure, grounded in event calculus principles. An event, in this context, is defined as a change in the type of spatial relationship, along with its relevant attributes.

Sensor data recorded over time are change into qualitative spatial information about monitored reality by the inference engine equipping sensor nodes, then transferred to the sink node following the communication protocol implemented. In this approach, sensing node where local spatial information is inferred and sink node where spatial information about the geometry of the extent of monitored phenomena is inferred, use the same structure and computing strategy.

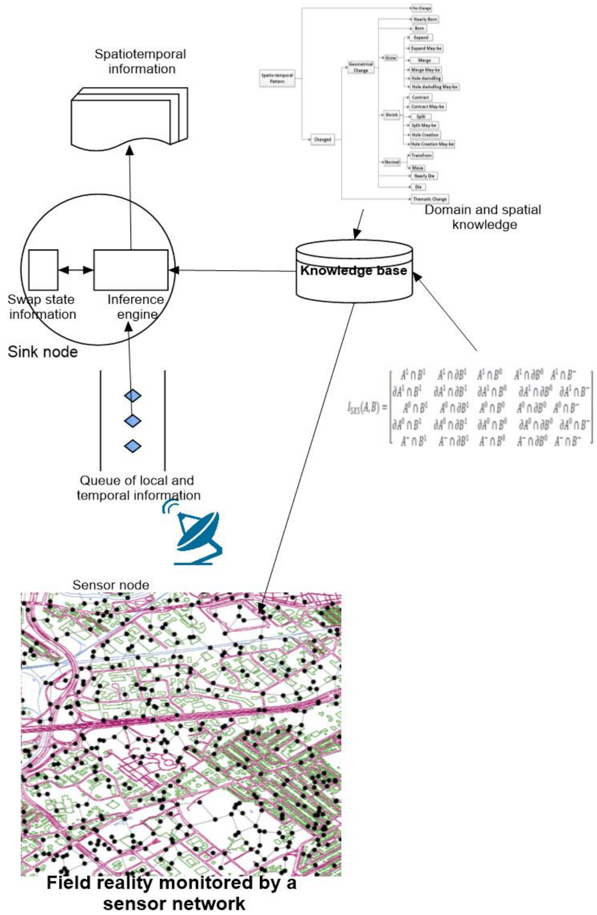


Figure 3. Simplified presentation of the reasoning procedure used for spatiotemporal reasoning from sensor data

3. Results and discussion

In the proposed approach, spatial computations based on sensor data are performed across the entire sensor network. Sensor data undergo a fuzzification process, defined according to the physical laws governing the monitored phenomena. The resulting fuzzy values are then transformed into qualitative spatial information, indicating the relative position (inside or outside) of each sensor with respect to the extent of the monitored phenomena. This serves as the starting point for computing spatial relations and dynamics.
We use a simulation case of air pollution in Quebec City to implement and evaluate the performance of the proposed approach. Figure 4 shows the NetLogo simulation window, in which the sensor network is displayed over a portion of Quebec City.
In figure 4, sensors within the kernel part are colored in red and labeled 1, those in the conjecture part are colored in orange and labeled 2 while those out of the pollution zone remain black.

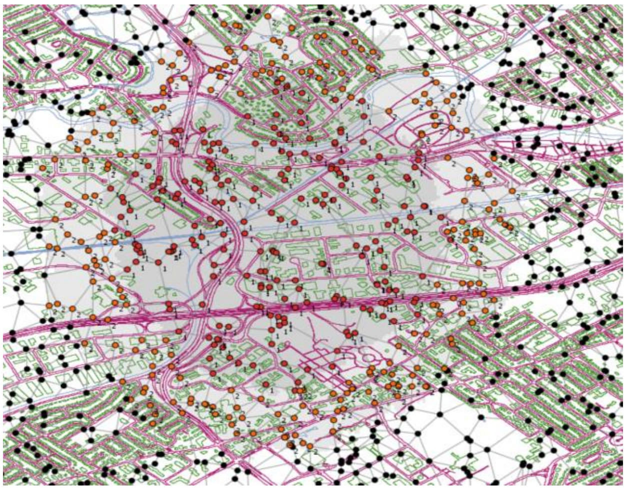


Figure 4. Excerpt of Quebec City covered by a SN showing a propagation of air pollution in gray and light gray for the kernel and conjecture part rescpectively (buildings in green, roads in purple and rivers in blue)

3.1 computing the geometry of sensed phenomenon and analysing spatial relationships

3.1.1 building fuzzy-crisp object form distributed information: By collaborating with their direct (one hop) neighbours, sensors are prone to know if their position is within the kernel the broad boundary and if they are close to the limit of these topological parts.

In this pervasive computing approach, each sensor sends to the sink node the inferred local spatial information, describing the relative position of its vicinity within the spatial extent of the monitored phenomenon at a given time. It is at the sink node that all this distributed qualitative spatial information is aggregated to construct the fuzzy-crisp object representing the geometry of the monitored phenomenon.

The boundaries shown in Figure 5 were plotted using a weighted approximation to illustrate a case in which the positions of the vertices differ from both the inner and outer boundaries corresponding to the sensor locations. Vertices are identified along the communication links established between these two positions (inner and outer), regardless of the topological region (kernel or conjecture) of the spatial extent for which the boundary is being established. For safety-critical applications, such as pollution monitoring, a maximalist approximation is appropriate, as errors in the solution design must be avoided. In this scenario, the spatial object modelling the monitored phenomenon may extend beyond its actual ground extent

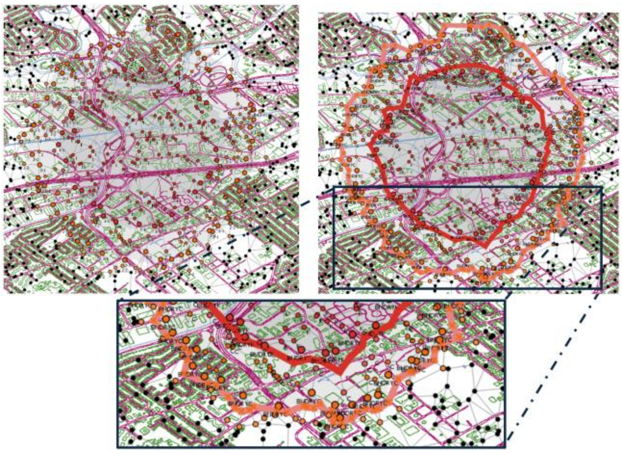


Figure 5. representation of the spatial extent of sensed pollution using a fuzzy-crisp region with a kernel limit (red) and a broad boundary limited by an orange line

Building the geometry of monitored phenomena is therefore tightly correlated with the deployment of SN. There is still considerable discussions about the optimal placement of sensors in a SN to capture error-free information about real world features (Doodman et al., 2025).

3.1.2 Computing fuzzy spatial relationships between built fuzzy-crisp spatial regions in the SN: In multisensory systems, when two phenomena A and B can be sensed all-over the SN extent, the proposed approach enables a collaborative reasoning from which each node can simultaneously infer to which of the 7 spatial statuses it belongs for A and for B. This information about the spatial statuses of each node about A and B detection are codified and sent to the sink node if this node detects at least A or B at a given time. The compiled information by the sink node is used to populate the intersection model ($I_{5x5}M$) from which the global description and qualification of inferred spatial relationship that holds at a given time.

For illustration we simulated a case of air pollution as A and windy conditions as B in the city of Quebec City to provide information about the spatial relationship between A and B to support decision-making process. Figure 6. Illustrates a case of disjoined phenomena detected by the SN.

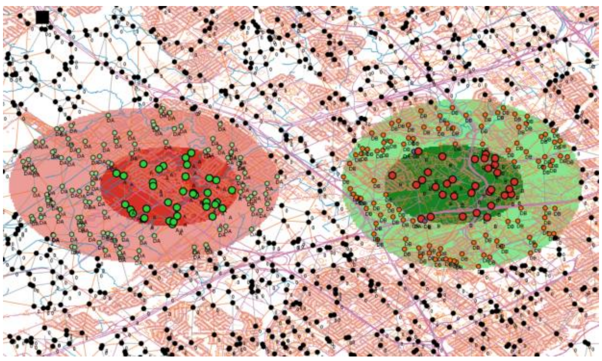


Figure 6. Excerpt of Quebec City (buildings in light red, roads in purple and rives in blue) where 2 disjoined phenomena A and B are detected by a SN

The detection of one of the phenomena A and B triggers the collaboration among linked one hop node to state on the corresponding spatial statues then this local spatial information is emitted towards the sink node. Once the whole set of distributed spatial statues is compiled by the sink node in the $I_{5x5}M$ the resulting intersection model is interpreted by the sink node and published to users for decision-making process. Figure 7. illustrates the resulting intersection model obtained from the computation of the situation presented in figure 6.

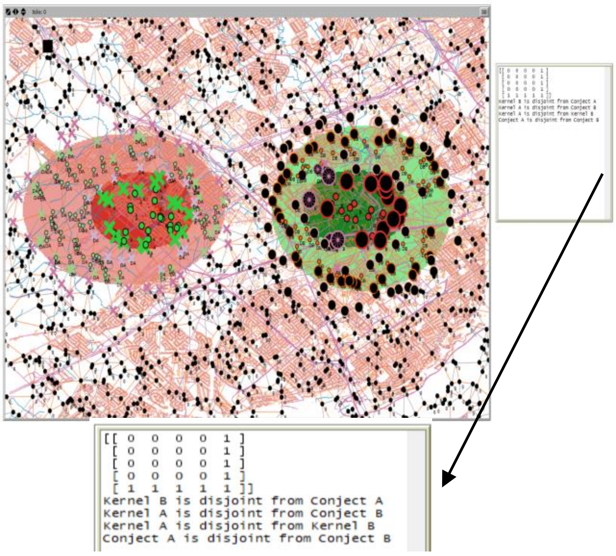


Figure 7. resulting intersection model $I_{5x5}M$ for a complete disjoint relationship at a given time

From the resulting model, the sensor system describes the scene as completely disjoint. The strategy for fighting against air pollution (A) can then be done considering that the polluted zone is out of wind influence (B). In such a system, instead of providing just a global representation of the scene, local spatial information for a specific position of interest can be provided to a user by sensors (see the symbology used in representing sensors of different category / status). Additional information such as the distance between the 2 zones may also be computed for safe field operations.
If subsequently, the air polluted area (A) is nearly overlapping the windy zone (B), the resulting information provided by the system will look as shown in figure 8.

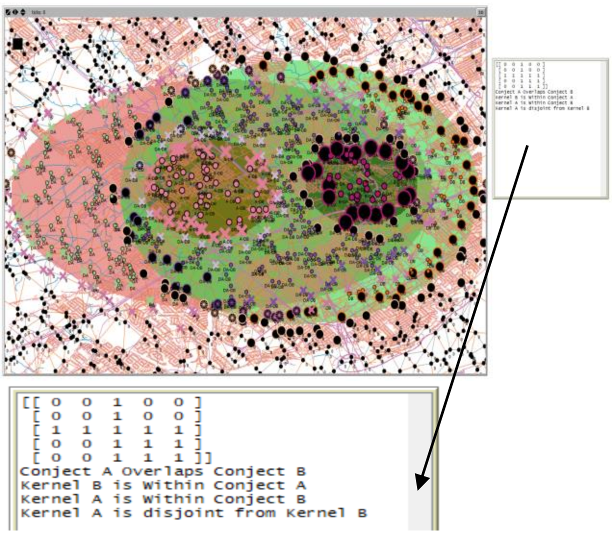


Figure 8. resulting intersection model $I_{5x5}M$ from sensor data for a case of nearly overlapping scene

Figure 8 shows the inferred $I_{5x5}M$ and its description, displayed in a output field of Netlogo beside window displaying the scene. The scene description is derived from the $I_{5x5}M$ structure. From the description derived from the $I_{5x5}M$ it is clear that: the conjecture of A overlaps the conjecture part of B, the Kernel of A is disjoined from that of B and the kernel of A and B are within the conjecture part of A and B; this is in accordance with what is sensed by the SN. In such situation, the decision makers can readjust their operating strategy accordingly.

3.2 Computing spatiotemporal changes about phenomenon with broad boundaries over sensor network extent

For dynamic phenomena, in the proposed event-rule-based approach each sensor computes ongoing spatial change over the flow of measured data; this is done when there is a significant change in data values which may lead to a change in sensor's spatial status. The current status of each sensor is compared to its previous status to state on event or ongoing process. On the thematic dimension this comparison can state on if the phenomenon is: starting/initiating, amplifying, decreasing or dying. The spatial correspondences of these thematic changes are related to the extent of monitored phenomena: appearing, expanding, shrinking/contracting moving or disappearing. This spatial dimension of changes is therefore computed through sensors collaboration with direct one hope neighbours based on their current statuses.
The approach was implemented the for a simulated case of changes happening in an evolving air pollution detection in Quebec City.
From distributed changes inferred by the nodes as nearly born for nodes in the conjecture (broad boundary) part and born for nodes in the kernel part, the sink node infers on the born /appearing of monitored phenomenon with its geometry as shown in figure 9.

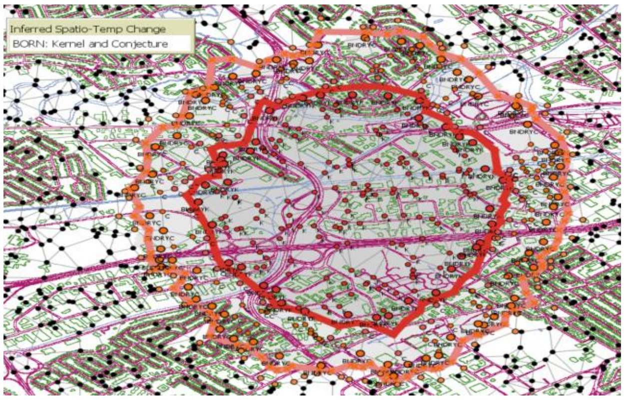


Figure 9. Initial detection of a simulated air pollution phenomenon in Quebec City; geometry made of 2 limits: kernel in red and conjecture in light red

If a pollution control operation is undertaken and there is a reduction in polluted area, the system infers the change as contacting and display the new area superposed on former polluted area as shown in figure 10. Former polluted area is represented using green colour and light green colour for kernel and conjecture limits respectively while the current extent is represented using red and light red colours for the kernel and conjecture parts respectively. Providing users with successive geometries about monitored phenomenon extent can help in evaluating the performance of the fighting strategy or readjust the resources mobilized.

As shown in Figure 10, each node retains its previous spatial status, which for the selected node here is “BNDRYK” corresponding to “boundary of the kernel”; for this node, the updated spatial status which is inferred from current measurement is “Outer”. The difference between the former and the actual status is used to infer on the type of spatial change; in this case the local spatial change corresponds to evol = “KShrk” indicating a Kernel shrinkage is occurring in the vicinity of the selected node. This will be the case for all the nodes over the SN. The approach can therefore provide users with localised et generalized spatiotemporal information.

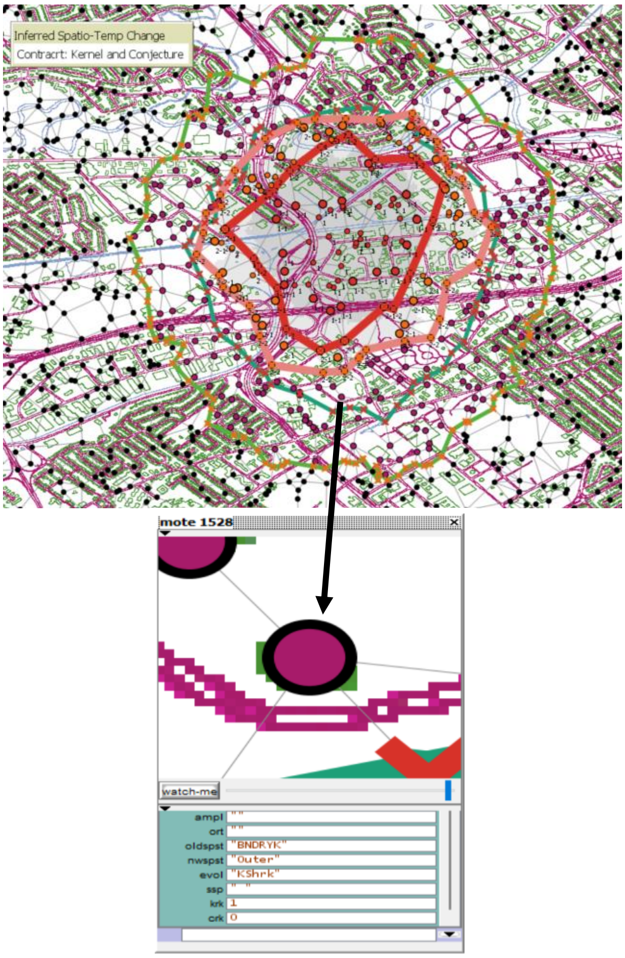


Figure 10. inferred contracting/shrinking change by the system with 2 consecutive spatial objects: green end light green limits for the initial extent and red and light red limits for actual kernel and conjecture extent respectively

The spatial pattern of local changes inferred over the SN is analysed to state on the nature of ongoing spatial change affecting the fuzzy-crisp region modelling the spatial extent of monitored phenomenon. As shown in figure 11, spatial changes inferred by sensors across the SN can be aggregated into 4 clusters: CExpd for conjecture expansion, KExpd for kernel expansion, CShrk for conjecture shrinkage and KShrk for kernel shrinkage. These change values which are displayed as label of sensors holding boundary position; they can be organized in two fronts: an expansion front made of KExpd and CExpd and a Shrinking front made of KShrk and CShrk; the existence of these 2 distinct fronts is the argument in inferring a moving change.

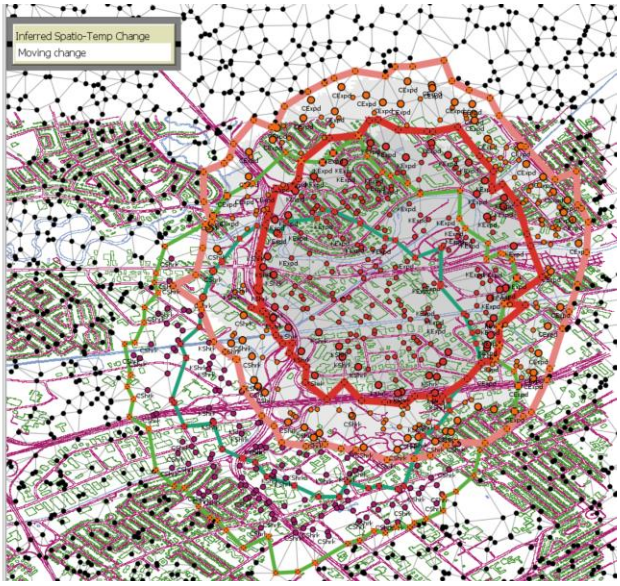


Figure 11. Moving change inferred showing the pattern of local changes inferred over de SN

The current results are based on a dense sensor network with the assumption that the topology of the SN overcomes field constraints related to observation and communication. The proposed approach should be tested on a real sensor network. Further works should focus on how qualitative spatial information inferred from sensor data should be formatted for easy transmission over the SN and towards the sink node.

4. Conclusion

In this paper, we design and implement a decentralized fuzzy spatial reasoning approach to compute spatiotemporal changes and topological relationships in dynamic phenomena with vague shapes, based on sensor network (SN) observations and measurements. The approach uses fuzzy spatial reasoning to construct fuzzy–crisp region objects representing large-scale phenomena with imprecise spatial boundaries. The reasoning rules are built on FESTCP and the $I_{5\times5}M$ matrix to model and infer spatiotemporal changes and topological relationships between fuzzy–crisp objects. The approach is evaluated through a simulated air pollution case study and performs well in providing both local and global spatiotemporal information for dynamic real-world phenomena, thereby supporting near real-time decision-making processes. Future work will focus on extending the proposed approach to model and reason about environmental phenomena with complex, vague spatial shapes. Also, the implementation of proposed approach in real SN is envisaged.

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