Modelling Vague Shape Dynamic Phenomena from Sensor Network data using a Decentralized Fuzzy Rule-Based Approach

Roger Cesarié Ntankouo Njila[1], Mir Abolfazl Mostafavi[1], Jean Brodeur[1]

[1]Centre de Recherche en Géomatique, 2314 Pavillon Casault; Université Laval, Québec, Canada, G1K 7P4
Email: roger-cesarie.ntankouo-njila.1@ulaval.ca, Mir-Abolfazl.Mostafavi@scg.ulaval.ca, recherchegeosemantic@videotron.ca

Abstract

Modelling dynamic phenomena of vague shape from sensor data is still a challenging problem for many applications. In this paper, we propose a decentralized fuzzy rule-based approach based on fuzzy object model to build a more realistic spatiotemporal representation for such phenomena. This approach has been successfully implemented in a simulation case of bushfire monitoring, showing advantages for spatial decision making in a disaster management context.

Keywords: *sensors, sensor data, fuzzy objects, disaster management, spatial decision support*

1. Introduction

Extracting geospatial information from geosensor data can help to better understand a complex phenomenon for real time decision making process (Sadeq *et al*. 2013). Several approaches are used for the extraction of geospatial information from sensor data. Many of these approaches are developed based on the assumption that monitored phenomena are of crisp shape with well-defined boundaries. However, many dynamic phenomena have vague spatial boundaries, and their accurate detection and extraction from sensor data is a challenging problem.

In this paper we propose a decentralized fuzzy rule-based approach to address this problem. In the proposed method, sensors detect vague shape phenomena using a fuzzy logic reasoning approach and collaborate with their neighboring sensors to infer vague spatial extent of the phenomena and its dynamics. We adopt Crisp-Fuzzy objects (Pauly and Schneider 2008) as a more realistic model for large scale and vague shape dynamic phenomena.

This paper is organized as follows. After a brief background presented in section 2, section 3 describes the proposed approach implemented in section 4 for a bushfire simulation case showing it applicability for real time spatial decision process in disaster management. Section 5 presents conclusions and future works.

2. Background

Spatial computing can be undertaken in a sensor system following a centralized (all data are sent to process center), a decentralized (located at sensor site or other site) or a hybrid approach (Chong and Kumar 2003). Crisp vector objects are extracted in the existing approaches using statistics or filters (Chintalapudi and Govindan 2003) or qualitative reasoning (Guan and Duckham 2009). Real-world phenomena are inherently uncertain (Carniel *et al*. 2015).

Crisp-Fuzzy objects model (Pauly and Schneider 2008) is an interesting candidate for the representation of such phenomenon. In this model the geometry of object is composed of a kernel and a conjecture part, the kernel part belongs definitely and always to the vague object but one can't say with certainty whether conjecture part considered as the broad boundary belongs to the vague object.

Fuzzy models are defined based on Fuzzy Set Theory that deals with inherent fuzziness and uncertainty of a phenomenon in real world through a membership function $(\boldsymbol{MF})$ (Ross 2010) determining the degree of belonging of an element to a set. $\boldsymbol{MF}$ is essential for defuzzyfication, it helps in reducing a fuzzy set to a crisp single-valued quantity, or to a crisp set (Ross 2010), thus given sensor data values, $\boldsymbol{MF}$ is used to infer the belonging of sensor positions to parts of the vague object $(\boldsymbol{Vobj})$.

The fuzzy spatiotemporal representation of a dynamic phenomenon (forest fire) extracted from sensor data represents an interesting tool for decision making. This can help for example to manage people evacuation to safe place or efficiently deploy resources for firefighting. This can also help individual users to answer to the questions such as: Is my location surely in, out, near or far from fire zone? Complete answer to such questions requires collaboration among sensors.

3. Presentation of the proposed approach

Sensors perform measurements over time, from the set of collected data at a given time, spatial computing can be undertaken in the sensor network (SN), building temporal spatial view of the phenomenon. This can be undertaken over time with changes detection to understand the dynamics of the phenomenon. This section presents the two reasoning stages implemented by sensor nodes to build a fuzzy spatiotemporal representation of a phenomenon from sensor data.

3.1 Stage-1: Local detection of phenomenon using three-valued logic

Using a built-in reasoning engine, each sensor evaluates its membership to different parts of the spatial extend of a dynamic phenomenon using a MF and the observed data at a given time. MF definition should cope with the semantics of sensor data and phenomenon (Ross 2010). For illustration, let's consider a sensor network recording temperature in an area under bushfire, considering the ontology of sensor data for fire monitoring (Gao et al. 2014), MF for such case can be of S shape as illustrated in Figure 1.

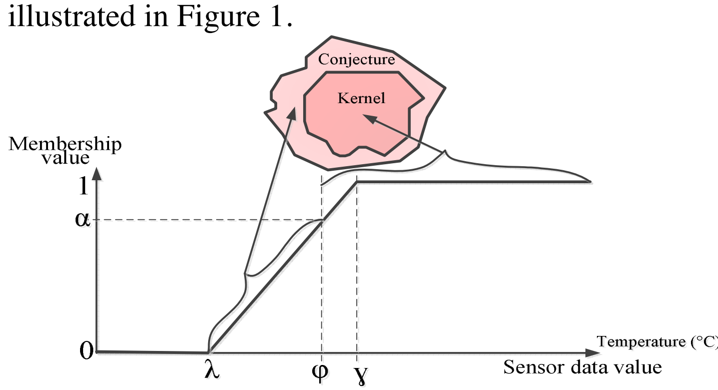

Figure 1 : S shape membership function for bushfire detection from sensed temperature.

Considering Sr as record value of sensor s at location $Loc(s)$ and time t, the membership function f defines μ the membership value of $Loc(s)$ as follows.

$$\mu = f\{Sr(Loc(s),t)\} : Sr \rightarrow [0,1] \qquad (1)$$

Considering the Crisp-Fuzzy object $(Vobj)$ representing the phenomenon, we use three-valued logic to define IF-Then rules used for defuzzyfication, these rules can be defined as follows:

$$IF\, \mu \geq \alpha\, Then\, (Loc(s),t) \in Kernel \qquad (2)$$

$$IF\; 0 < \mu < \alpha\, Then\, (Loc(s),t) \in Conjecture \qquad (3)$$

$$IF\; \mu = 0\, Then\, (Loc(s),t) \in Outside \qquad (4)$$

At this stage, sensors are aware of the presence or absence of phenomenon at their location but no information about the spatial extent of the phenomenon is inferred.

3.2 Stage-2: collaborative spatial reasoning for the extraction of vague object representing the phenomena

A sensor detecting the phenomenon (Kernel or Conjecture) sends queries to its one hop (directly linked) neighbors named N(s) through the communication mesh (Gabriel Graph) materialized by links between nodes, as shown in Figure 2. Nodes sending queries provide each of their respondents with the required information: Identification, location, detection value at given time. The general form of query is as follows:

$$Type\_Query : My\_Id = ii, My\_loc = xy, My\_detection = type, Time = tt, ?Your\_Id, ?Your\_loc, \ ?Your\_detection \quad (5)$$

Two types of queries are propagated in the network, $\boldsymbol{KQuery}$ and $\boldsymbol{CQuery}$ for query with $\boldsymbol{My\_detction = Kernel}$ and $\boldsymbol{Conjecture}$ respectively. Each node not detecting the phenomenon (outside) by receiving even one query ($\boldsymbol{KQuery}$ or $\boldsymbol{CQuery}$), holds an outer-bordering position as shown in Table 1. Querying node infers on it possible inner-bordering position from the set of received answers, then determines closest vertices halfway to linked outer-bordering nodes. Joining the set of identified vertices can be undertaken by leads nodes, to build kernel and conjecture boundaries at a given time. Nodes are labeled for easy reading/computing with 2 characters denoting phenomenon detection and bordering position respectively.

Table 1 : Relative position of nodes according to parts of the monitored phenomenon.

Phenomenon part detection	Type of query or answer received	Relative position	Label-value
Kernel	Only $\boldsymbol{KQuery}$	*Kernel - inner*	1 – 0
Kernel	Even one $\boldsymbol{CQuery}$ or one answer from Outer node	*Inner - Kernel - boundary*	1 – 1
Conjecture/Outside	Even one $\boldsymbol{KQuery}$	*Outer - Kernel - boundary*	1 – 2
Conjecture	Only $\boldsymbol{CQuery}$	*Conjecture - Inner*	2 – 0
Conjecture	Receiving answer from an Outer node	*Inner - Conjecture - boundary*	2 – 1
Outside	Even one $\boldsymbol{CQuery}$	*Outer - Conjecture - boundary*	2 – 2
Outside	No query	*Outer*	0 – 0

In dynamic phenomena, occurring changes can modify the relative position of nodes over time, thus changing the spatial extent of the phenomenon (expansion, narrowing...).

4. Modeling a monitored bushfire for spatial decision support

Here we present a bushfire case study to illustrate the applicability of the proposed method for the extraction of a fuzzy spatiotemporal representation of the phenomena using sensor data. As presented in Figure 2, The monitored phenomena is made of Kernel (pink) and Conjecture (yellow) parts in an area with road and water networks (magenta and blue respectively). Sensors are represented by dot and are linked together by a communication mesh.

Information on the spatial extent of kernel and conjecture parts or about their spatial evolution can help in managing the resource (human/material) to be mobilized while fighting against fire. Sensors are also labeled with information which can be used in strategic decision making process as evacuation strategy of endangered population by selection the appropriate road linking to safe area (no label for 0 – 0 as mentioned in Table 1). Also, 2 – 2 labeled positions which are out of the fire area express the proximity to area where one may meet fire.

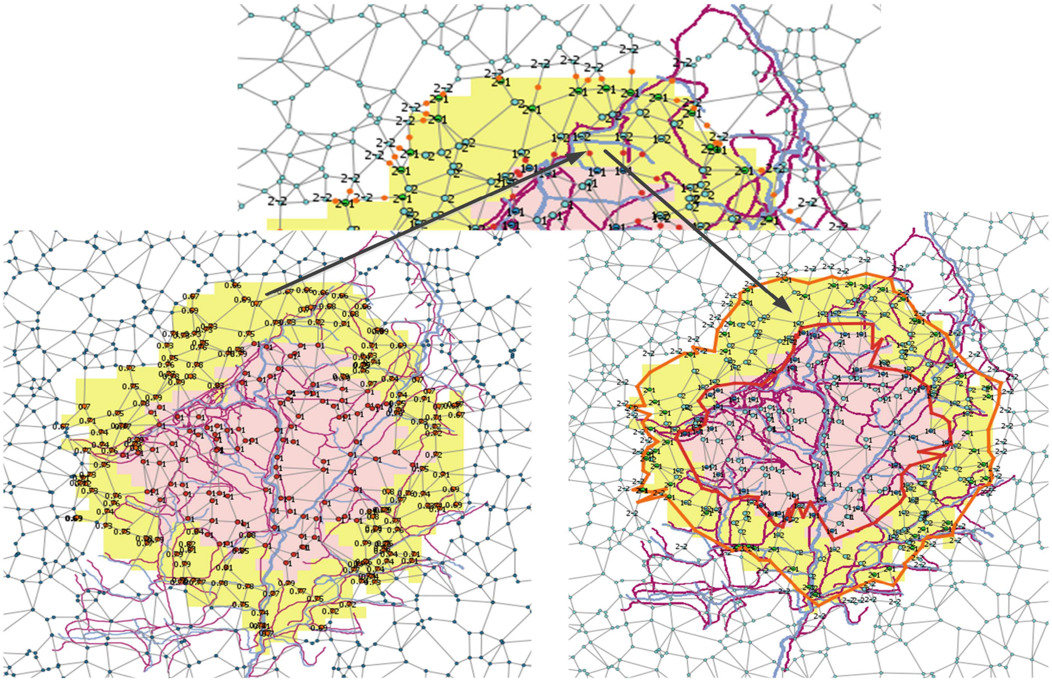

Figure 2 : Extracting fuzzy spatiotemporal representation of bushfire.

5. Conclusions and future works

In this paper we have presented a fuzzy rule-based approach that integrates sensor data describing phenomena of vague shape. Semantic information on sensors are used to establish fuzzy rules used by sensor to reason on their membership value and collaboratively infer a more realistic spatiotemporal representation of a vague dynamic phenomenon. We have also presented how these representations can be used for spatial decision making process for a disaster management case. For future works, we intend to consider heterogeneities in sensor data and observations context in the reasoning approach.

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