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Semantic reasoning system for monitoring natural disasters based on GeoSPARQL ontology and satellite images (Study case: flood prone areas of Shiraz city)

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Abstract

Accurate and automated classification of satellite images is crucial for disaster management and monitoring climate change. It is important not only to identify objects and entities in satellite images but also to reason about them and respond to queries from human operators to guide decision-making processes. Recent studies by climate researchers indicate that several areas in Shiraz are at risk of flooding. The Shiraz flood scenario is a real possibility. We have defined a disaster scenario in which the central part of Shiraz is mostly covered by water. The main objective of this research is to display the geometry of regions on a map, allowing for questions related to topology and neighborhood to be answered. Our research presents a framework for transferring satellite image data to an interactive map that is ready for mining. To obtain a searchable map from satellite data, a CNN classifier sensitive to image features is used to label regions. The framework's capabilities in terms of route connectivity are demonstrated. The features are represented in an ontology that extends the existing GeoSPARQL ontology, allowing the system to automatically search for classified regions based on specific environmental criteria. We have demonstrated how semantically enriching the representation of regions in OntoCity can improve search time, including region revision and co-routing, by enabling the system to automatically find options for regions. The SemCityMap framework can now serve as a tool for better decision-making and situational awareness.

Keywords: semantic reasoning, ontology, satellite images, monitoring of natural disasters
2020 MSC: 62R07

1 Introduction

Ontologies have been utilized as a semantic representation model in both the geographic information system (GIS) and remote sensing (RS) fields. Semantic models, by definition, are a discourse field consisting of related concepts, their relationships, and constraints. Ontological representations can bridge the semantic gap between levels of data abstraction. In GIS, this can range from processing digital satellite image data of a landscape to representing symbolic information in the form of objects or physical entities in that landscape [15]. Ontologies facilitate semantic

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interoperability through the reusability of knowledge and are therefore useful in representing various domains. For instance, in GIS research, ontologies serve multiple purposes, including image classification, information retrieval, and decision-making processes [2]. In image classification, which is an essential process in earth-related applications that use satellite image data, ontologies semantically relate image data to related objects and enhance classification results. Reasoning methods utilize ontological relationships to interpret explicit and implicit information. For instance, when a user provides a concept, an ontology-based reasoning process that understands ontology languages can retrieve more general or specific concepts by utilizing the underlying relationships between them [13].

To specify more features about a concept, it can be related to other concepts, creating more complex relationships [3]. For instance, consider an ontology that provides concepts related to land, including river, building, road, bridge, and so on. The concept of bridge may be more geographically related to the concept of surface, as bridges are often built over rivers to connect two banks. By adding this relationship to the ontology, along with additional geographic, spatial, or topographical information, a reasoner can identify which items on the map this relationship applies to and, therefore, identify an object such as a bridge. The language used provides a high-level description of what can be found on a map and offers knowledge and information about the current situation. Explicitly defining concepts and their relationships supports the reusability of ontological information [12]. Ontological reasoning heavily relies on the accurate definition of concepts and their relationships. It can leverage the general applicability of ontologies and provide more information beyond a specific domain [9]. This paper explains how OntoCity, the primary representation model in our study, utilizes ontology patterns to assist the reasoner in retrieving valuable information for the user.

2 Previous works

2.1 Distributed reasoning in ontologies

Various frameworks have been proposed for distributed reasoning in ontologies, including descriptive logic and description logic. Some researchers have utilized these frameworks to develop algorithms for distributed reasoning, while others have expanded and implemented centralized reasoning methods in a distributed manner across multiple ontologies. The study [11] proposes a distributed inference approach to address major issues in large-scale data. It aims to reduce the time spent on inference processing and the need for scalable computing capabilities for large data sets. Additionally, it offers data augmentation with SIM construction (sparse index method) and ATC (alleged triple construction) to address the difficulty in extracting suitable triples for suitable inferences. The text also mentions efficient processing of user queries and storage space. The authors of two studies [1, 6] proposed using ontologies to improve object-based semantic classification. In the first study, a knowledge-oriented methodology was introduced to express the objects, their size, and their spatial relations. The second study introduced an ontology-based solution for classifying satellite ocean images, using an ontology that provides high- and low-level features of regions extracted from an ocean. In addition to ontology languages such as Resource Description Framework (RDF) and Web Ontology Language (OWL), ontologies enable the use of more constraints in defining concepts. These constraints are more understandable to reasoners and can retrieve more explicit information about a specific area. For instance, the method described in the research [10] can obtain geographical data by utilizing a qualitative representation. In this representation, spatial and directional relationships are defined in a clear and understandable manner by the qualitative reasoner.

In addition to their role in improving the analysis of earth-related data, as demonstrated in the aforementioned research paper, ontologies have recently been increasingly utilized for specific applications, such as emergency management, including the rescue and relief of people affected by natural disasters. The field of natural disasters has seen a significant amount of work based on ontologies.

Ontologies have a semantically interactive feature that can increase the probability of retrieving necessary information. For instance, in [16], an ontology model was proposed to present events and the required actions for specific damage conditions. In another study [5], an ontology developed based on SUMO was introduced to model an emergency rescue pattern that is automatically generated based on a given context.

The study [5] describes the OntoFire ontology, which is part of a portal that focuses on rogue fires and provides various services, such as automatically generated navigation based on discovered relationships between assumed data. Additionally, the study [8] introduces FloodOntology, which is used for flood prediction and consists of entities related to sensing elements, such as hydrological/hydraulic parameters used to predict the time and duration of floods. The purpose of the study [4] is to create an ontological data model that can aid in responding to urban flood disasters. The Flood Disaster Support Ontology (FDSO) serves as a data model that can be utilized by various organizations and agents at different levels of administrative organizations involved in the flood disaster management process. The ontology was developed by integrating two existing methods, the YAMO method for ontology development and NeOn. The ontology underwent both syntactic and semantic evaluations. Syntactic evaluation was conducted using OOPS!, an ontology trap scanner, while semantic evaluation was performed through SPARQL queries.

The article [7] presents an ontology-based assessment framework for efficient flood disaster location queries. The framework includes a reasoning system with spatial and feature patterns to respond to the generated query. The study performs hierarchical and semantic data analysis using data from urban flood disaster environmental conditions. Finally, data evaluation is done by visualizing data and correlation patterns to answer higher-level queries. The study proposes an ontology-based evaluation framework that was simulated using the MATLAB environment. The results indicate that the proposed framework outperforms existing frameworks, with an average query response time of less than 7 seconds. Additionally, the study [14] presents a basic ontology framework for disaster management called the Disaster Management Ontology (DMO), which is based on the NDMA responsibility matrix. The DMO helps distribute tasks among necessary authorities at different stages of a disaster and provides a knowledge-based decision support system for financial assistance to victims. The proposed Disaster Management Organization (DMO) utilizes ontology for knowledge integration and as a working platform for reasoners. It also includes a decision support system (DSS) rule set written in Semantic Web Rule Language (SWRL), which is based on first-order logic (FOL) concepts. It also includes a decision support system (DSS) rule set written in Semantic Web Rule Language (SWRL), which is based on first-order logic (FOL) concepts. It also includes a decision support system (DSS) rule set written in Semantic Web Rule Language (SWRL), which is based on first-order logic (FOL) concepts. OntoGraph, a class representation of the taxonomy, enhances user interaction with the taxonomy.

Semantic interoperability is crucial in articles that involve sharing various types of data and reasoning on it. To achieve better semantic interoperability, it is essential to design ontologies that adhere to common ontology patterns, which typically rely on higher-level ontologies. Unfortunately, many of the ontologies used in natural disaster scenarios are designed in an impromptu manner and are not based on higher-level ontologies.

2.2 Suggested method

This study focuses on using existing land ontologies to enable semantic interoperability in land-related domains. The proposed ontology, OntoCity, is an extension of the GeoSPARQL ontology by the Open Geospatial Consortium (OGC). The appendix explains how this ontology supports the use of semantically enriched data. The study implements map classification through the use of a Convolutional Neural Network (CNN) based on seven primary categories of labels: plants, land, road, building, water, road, and parking lot. The input of the CNN is the area surrounding the pixel to be classified. The CNN output is connected to the maximum smooth layer for final classification. A single-layer CNN is used on a 25×25 input patch with 50 filters of size 11 and pooling dimension 5. The hyperparameters were selected to extract a 3×3 output from the CNN. The maximum smooth layer was set to 500 hidden units. The training, validation, and test sets were created by randomly selecting 1000 input patches of size 25×25 from each of the 7 classes and dividing them into 80/10/10 slices. The classification results are presented for the test set. After classifying the entire map, we obtain the segmented regions to be used later by applying the SLIC segmentation algorithm and merging the pixels based on their classification.

2.3 Modeling in ontologies

To facilitate intelligent reasoning in natural disaster management using image data, a representation model that expresses data and relationships at a more abstract, symbolic level is necessary. To this end, we have developed an ontology called OntoCity. OntoCity is based on GeoSPARQL, which is a standard term proposed by OGC for spatial data in RDF. This enables qualitative spatial reasoning for this type of data. OntoCity is a tool designed to represent all structural aspects of a city, including its components, types (e.g. natural or artificial), and relationships (e.g. spatial relationships, capabilities, etc.) that may be used for disaster relief. The following sections describe the structure of GeoSPARQL and its annex formed in OntoCity.

2.3.1 GeoSPARQL

GeoSPARQL provides a common basis for defining any spatial object that has a geometry in the physical world. The class responsible for displaying such features in the geospatial domain is called geos: Feature, of which the goes: SpatialObject class is a subclass. The geos: hasgeometry property connects each instance of this class property to another instance that belongs to the goes:Geometry class.

$$Geos : feature \sqsubseteq \exists geos : hasGeometry.geos : Geometry$$

Using the geos:asWKT attribute, each geometry represents all boundaries (internal and external) of the object as a WKT (well-known text) that points to a precision value that specifies a list of coordinates that define the boundary:

$$Geos : geometry \sqsubseteq \exists geos : asWKT.rdfs : Literal$$

The geos:Geometry class has its own class to define specific geometries such as polygons, rectangles, etc. as its subclasses.

In addition, GeoSPARQL provides a set of specifications that qualitatively represent the spatial relationships defined in RCC-8. According to RCC-8, any spatial relationship between two spatial objects can be represented in one of the 8 basic RCC relationships as shown in Figure 1.

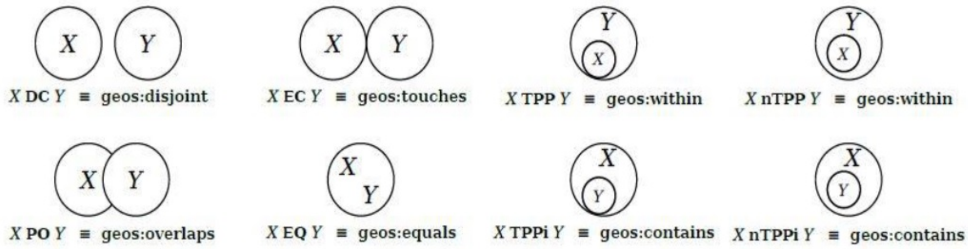


Figure 1: RCC-8 Spatial Relations defined in GeoSPARQL, where DC= Disjoint, EC= Fully Connected, TPP= Tangent Correct Segment, nTTP= Non-tangent Correct Segment, PO= Relatively Overlapping, EQ= Equal, TPPi= Inverse Tangent Correct Segment, nTTPi= inverse of the non-tangent correct segment.

2.3.2 Building OntoCity with GeoSPARQL extension

During the development of OntoCity, we utilized the DOLCE+DnS Ultralite ontology. OntoCity extends the GeoSPARQL ontology in three ways: 1) Refactoring spatial relationships to determine object intersection, 2) Utilizing the geos:Feature classification to represent city areas and structures with tags such as buildings, rivers, and parking lots, and 3) Establishing path connectivity. A region can also represent a path, which is a transportation route located between two other regions. Our definition of path connectivity relies on the fact that region x is connected to region y via path z if and only if region y is also connected to region x via the same path.

3 Filling OntoCity for a specific disaster

In order to clarify how ontocity is used, and to what extent the system is able to understand raw satellite image data, we briefly discuss the details of the dataset and classification processes.

3.1 Data set

To evaluate the effectiveness of regional recovery and routing processes, we created a disaster scenario that involved rescue services. To simplify the scenario, we used a one-dimensional configuration for a self-navigating drone, which is represented as a three-dimensional point in space. The configuration space X is represented as a three-dimensional space, with limited numerical ranges for the x, y, and z coordinates, depending on the environment's width, length, and height. The available satellite data pertains to the central part of Shiraz, with geographical coordinates of 29 degrees 36 minutes north and 52 degrees 32 minutes east, and varying heights above sea level ranging from 1480 to 1670 meters in different parts of the city. Shiraz city experiences an average temperature of 30°C in summer, 5°C in winter, 17°C in spring, and 20°C in autumn, with an annual average temperature of 18°C.The city receives an annual rainfall of 337.8 mm. Currently, Shiraz is experiencing flooding, and the rescue team may receive various requests depending on the environmental conditions. For instance, a request may be to identify safe areas around flooded or hazardous zones (watershed posting) where people may require assistance. The rescue team may need to determine feasible routes to these areas that only pass through safe zones. The system presented here utilizes multiband satellite image data for both classification and visualization. These data are presented in two forms: geometrically corrected images and reconstructed 3D meshes. The dataset comprises of 7 primary bands and 7 dummy bands. The image data has a resolution of half a million pixels. The images are corrected and referenced to real GIS data. Table 1 provides a summary of the color bands.

For visualization, the generated 3D mesh data is used to allow the user to review the area from different perspectives.

Table 1: Spectral bands used in multispectral corrected images

Description	**Bandwidth (nm)**	**Bond**
Plant types, soil, and urban features	630–690	Red
Water, oil stains, plants and man-made features	510–580	Green
Shadows, soil, vegetation and man-made features	450–510	Blue
Soil, low foliage, wood, pine foliage	585–625	Yellow
Shallow waters, airborne particles, dust and smoke	400–450	Coastal
Band of fake images (green, blue, beach)	400–580	Seabed
Plant health, shorelines, biomass, plant	770–895	NIR1 (near infrared)
Similar to NIR1	860–1040	NIR2
High resolution pan and low resolution multispectral	450–800	Pansharpened
Band of fake images (NIR1, yellow and red border)	585–625, 705–745, 770–895	Soil
Fake images band (NIR2, yellow and coastal)	400–450, 585–625, 860–1040	Land cover
A mixture of visible light in a gray scale	450–800	Panoramic
Plant changes	705–745	Red border
Fake image band	450–510, 510–580, 770–895	Plant
Digital surface model	–	DSM

3.2 Classification and segmentation

The classification of maps is accomplished through the use of a Convolutional Neural Network (CNN) that is based on seven primary categories of labels: vegetation, land, railway, building, water, road, and parking lot. The input of the CNN is the area surrounding the pixel to be classified. The final classification is achieved by connecting the maximum smooth layer to the CNN output. In this study, a single-layer CNN with 50 filters of size 11 and a pooling dimension of 5 is used on a 25×25 input patch. The hyperparameters were selected to extract a 3×3 output from the CNN. The maximum smooth layer was set to 500 hidden units. The training, validation, and test sets were created by randomly selecting 1000 input patches of size 25×25 from each of the 7 classes and dividing them into 80/10/10 slices. The classification results for the test set are presented in Section 6.2.1. After classifying the entire map, the SLIC segmentation algorithm is used to obtain segmented regions, which are then merged using the pix classification. Please refer to Fig. 2. It is important to note that the term 'segmentation' in this context refers specifically to the SLIC segmentation algorithm and is distinct from instances of the onto:segment class defined in the ontology. The objective of merging regions is to decrease the number of regions and arrive at regions that more accurately represent real-world regions/objects.

3.3 OntoCity population

The ONTOCITY population comprises distinct processes for region, sector, event, and path assignment instantiation, which are completed entirely offline. In the following section, we describe the process of ontology population using Shiraz satellite data. The classification applied to the satellite data resulted in 115,000 labeled regions. Before populating ONTOCITY with these regions, mutually exclusive segments (instances of the ONTOCITY:SEGMENT class) must be generated to cover all parts of the city. We determined that a size of 1000×1000 pixels for each section is suitable for the complexity of the process and computational reasoning, based on the size of the map and the number of classified areas. The map is divided into 256 (16×16) sections, each containing around 470–410 regions. This is a computationally reasonable number of regions, particularly for the geometric/spatial calculations required in some welds. The ontology population process also involves calculating spatial relationships between each pair of regions within a segment. Regarding segmentation (ontocity:segment, not the segmentation process in the classification phase), the time required for geometry calculations on the map is significantly reduced. Each geometric calculation takes an average of 0.0014 seconds on a computer with the following specifications: Intel Core processor with a frequency of 2.6 GHz, 64-bit architecture, 16 GB of memory, and Linux operating system. On average, each section takes 110 seconds to calculate, resulting in a total of approximately 8 hours for a map consisting of 256 sections.

The next step that occurs offline (i.e., not during runtime) is the instantiation of classes that belong to the path binding pattern. The connectivity pattern is used to define a new capability for certain regions in terms of route connectivity. To illustrate, consider the blue area and the bridges shown in Figure 3. Instances of classes in the path connectivity pattern improve the performance of the routing process within a highly constrained environment. For instance, a region labeled as a road, which is connected to a water region and located between (connecting) at least

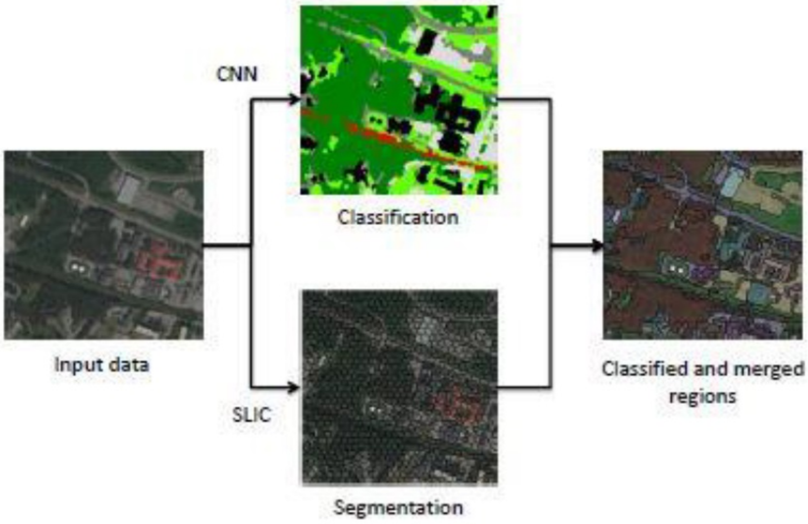


Figure 2: Merged classified regions, averaging the classification results (black = building, dark green = vegetation, light green = ground, gray = road, red = railway) over all classified pixels in each region, from a basic SLIC segmentation. are obtained Regions are merged if the average classification certainties for two connected regions are both above a certain threshold.

two distinct edge regions, can be relabeled as a bridge in its ontology. To identify such regions, we need to perform a search that includes all the aforementioned spatial criteria. Therefore, we must first define what is meant by the border area. The border area is the region that is connected to a blue area (i.e., geos:touches).

$$Shore = \{r_i \in \mathcal{R}_i | \mathcal{R}_i \sqsubseteq ontocity : GroundArea \ \wedge \exists r_j \in \mathcal{R}_j \sqsubseteq ontocity : WaterArea \wedge (r_i, r_j) \in \mathcal{S} \sqsubseteq geos : touches\}$$

Considering all examples of the border region, we finally define the associated bridges as:

$$Bridge = \{r_i \in \mathcal{R}_i | \mathcal{R}_i \sqsubseteq ontocity : Road \ \wedge \exists r_j \in \mathcal{R}_j \sqsubseteq ontocity : WaterArea \wedge (r_i, r_j) \in \mathcal{S} \sqsubseteq geos : touches$$
$$\exists r_{s1} \in Shore \wedge \exists r_{s2} \in Shore \wedge r_{s1} \neq r_{s1} \wedge (r_i, r_{s1}) \in \mathcal{S} \sqsubseteq geos : touches \wedge (r_i, r_{s2}) \in \mathcal{S} \sqsubseteq geos : touches\}$$

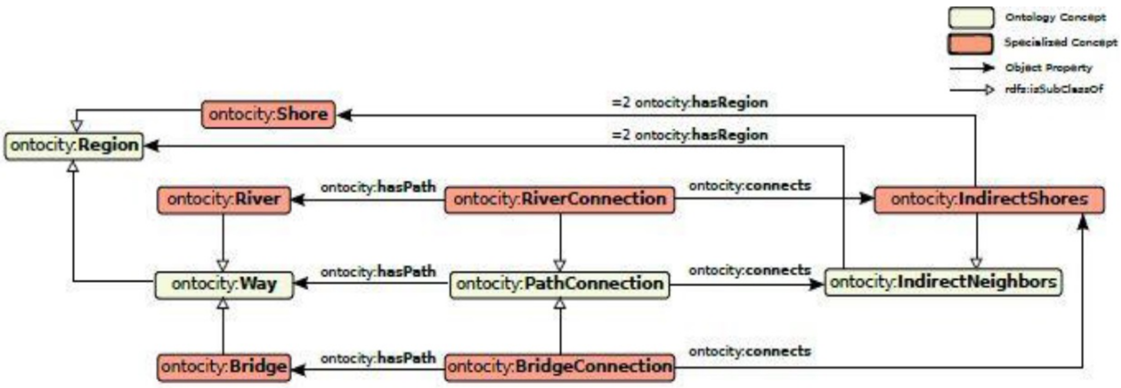


Figure 3: Path Connection attachment in OntoCity - Example of a road and a bridge

This paper focuses on the flood scenario. Therefore, it is sufficient to relabel areas that can also function as bridges over water. It is possible to apply Joyesh's argument and definition to other regions to obtain new labels that can be used in different scenarios. The labeling process is carried out on the central part of the map, which is mostly surrounded by water and is therefore highly susceptible to damage in the event of a flood. As previously mentioned, another offline process in ontocity instantiation involves representing events that occurred in various locations. Ontocity presents the results of this simulator in multiple polygons. If the area is designated as 'without water', the router will find a route that includes bridges, which is irrelevant in a flood situation since bridges may also be submerged.

Figure 4: Darvazeh Quran area, in flooded and non-flooded condition

a) Non-flood situation: the path finder is able to find a path using a bridge with a ”no water” adverb;

b) Flooded situation: the router is unable to find a route because the destination point is located in the flooded area.

The system’s densely populated ontology includes regions, path connections, and flood zones. This allows users, such as rescue teams, to customize the map to their needs when facing different environmental conditions. For instance, a rescue team may need to locate non-flooded areas within a range of 100 to 1000 meters from a flood point (p_f) on the map. They can then send a drone to check if anyone is stranded in those areas. The search can be expanded to include spatial features of the found areas. For instance, if a helicopter needs to be dispatched, the found areas should have location characteristics that are close to or connected with at least one large area of land where the helicopter can land.

$$\begin{aligned} Non-Flood-Region = \{ r_i \in \mathcal{R}_i | \mathcal{R}_i \sqsubseteq ontocity: Region \ \wedge \mathcal{R}_j \not\sqsubseteq ontocity: WaterArea \wedge \\ 100m \leq distance(p_f, r_i) \leq 1000m \wedge \nexists a \in ontocity: Area \wedge \\ (r_i, a) \in ontocity: intersects \} \end{aligned}$$

$$\begin{aligned} Non-Flood-Region = \{ r_i \in \mathcal{R}_i | \mathcal{R}_i \sqsubseteq ontocity: Region \ \wedge \mathcal{R}_j \not\sqsubseteq ontocity: WaterArea \wedge \\ 100m \leq distance(p_f, r_i) \leq 1000m \wedge \nexists a \in ontocity: Area \wedge \\ (r_i, a) \in ontocity: intersects \exists r_j \in \mathcal{R}_j \sqsubseteq ontocity: GroundArea \wedge \\ 4m^2 < size(r_j) \wedge (r_i, r_j) \in \mathcal{S} \sqsubseteq ontocity: touches \} \end{aligned}$$

3.4 Boiling time

In rescue scenarios, the most important factor is the response time to the boils. The number of available zones is the main factor that affects response time. To limit the number of candidate regions for fusions, a number constraint should be applied to exclude as many regions as possible. One of the essential criteria is the distances determined in welding. The greater the distance, the more areas that need to be processed. Although users determine the distances, other factors can significantly impact response time during the search exclusion process.

Table 2 shows three different setups for the same set of welds and their role in reducing welding response time.

The first setup is segmentation. This operator enables the exclusion of all regions belonging to unrelated segments by first reviewing the relevant instances of the ontocity:segment class.

Next, the zone types are separated. In welding, it is common to consider different zone types, such as water zones and land zones. To improve clarity, it is recommended to create a separate list of zones for each section, rather than a long list of regions regardless of their type. Only regions that are relevant to the specific task should be considered, while others can be ignored.

Additionally, it is important to exclude flooded areas before proceeding with geometric or spatial calculations.

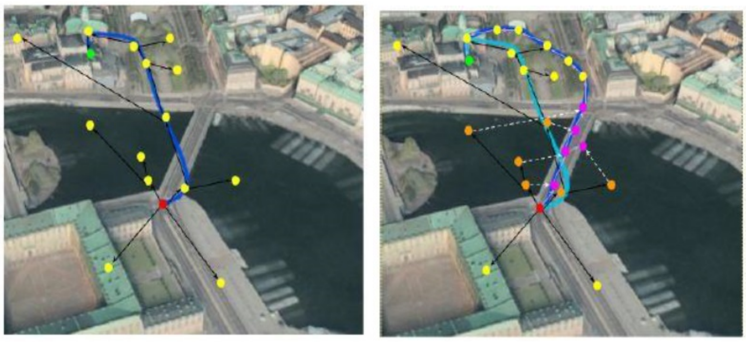
Table 2: The average response time of Jaish with and without the criteria mentioned in Jaish. The average value of each time is calculated during the execution of 50 different weldings

Exclusion of the flood zone	**Separation of area types**	**Segmentation**	
1.69 seconds	1.34 seconds	3 seconds	with time to search
2.71 seconds	13.52seconds	67 seconds	without time to search

To measure the average reaction time in both conditions (with and without the criterion), we conducted 50 runs for each criterion (refer to Table 3). We studied the role of two factors, independent of each other, in addition to the segmentation factor that was always considered. It is observed that the application of any factor in welding leads to the exclusion of some areas, which subsequently shortens the welding time.

Once the areas matching the desired criteria have been identified, the rescue team may require information on possible routes that only pass through safe areas.

Figure 5a illustrates a path connecting two points (Xinit in red and Xgoal in green) by crossing the river. However, the routing process encounters difficulties in finding a path due to the majority of samples being located in the forbidden blue areas, which are larger in size. However, as shown in Figure 5b, the routing process has replaced samples taken from the blue area (Xrand in orange) with samples taken from the bridge (Xalt in pink) as an alternative for the ontocity:water class.



(a) (b)

Figure 5: Routing with adverbs. Prototypes are red, green and yellow. The generated collision-free path is in dark blue. A) adverb: height of regions; b) Adverb: blue areas. Invalid samples are in orange and their substitutes are in pink.

RRT appendices were implemented for 70 different route problems with varying starting and destination points in central Shiraz. Table 3 displays the success rate with and without ontology reasoning during the routing tree construction process. The incorporation of semantics into the route generation process increased the success rate from 24.2% (17 out of 70 hits) to 91% (64 out of 70 hits) within a 10-second time frame for routing. The generation of a route without the use of ontology approaches the upper limit of the planning process in terms of time.

Table 3: Success rate with and without the use of ontology reasoning during the routing tree construction process

With the model of ontology	**Without ontology model**	
91%	24.2%	Success rate
68.0 seconds	8.4 seconds	Average execution time

4 Results and discussion

Our proposed framework utilizes a convolutional neural network (CNN) to rapidly classify map entities into predefined basic categories such as roads, buildings, and trees. Additional information from existing sources is then incorporated to extract addresses, features, and other high-level information. The reasoning framework utilizes ontologies to organize information, combining application environment knowledge in the form of ontology patterns with current situational information extracted from satellite imagery. This enables the system to effectively respond to high-level queries regarding the current state and state on the map. Fusions can contain concepts that do not directly correspond to the original labels and may also include characteristics of the pre-disaster situation due to relevant ontological reasoning. Fusions can contain concepts that do not directly correspond to the original labels and may also include characteristics of the pre-disaster situation due to relevant ontological reasoning. It is important to note that they can also contain complex combinations of other states. Fusions can contain concepts that do not directly correspond to the original labels and may also include characteristics of the pre-disaster situation due to relevant ontological reasoning.

The design of the ontology of Shiraz city, which was done by Porotege software:

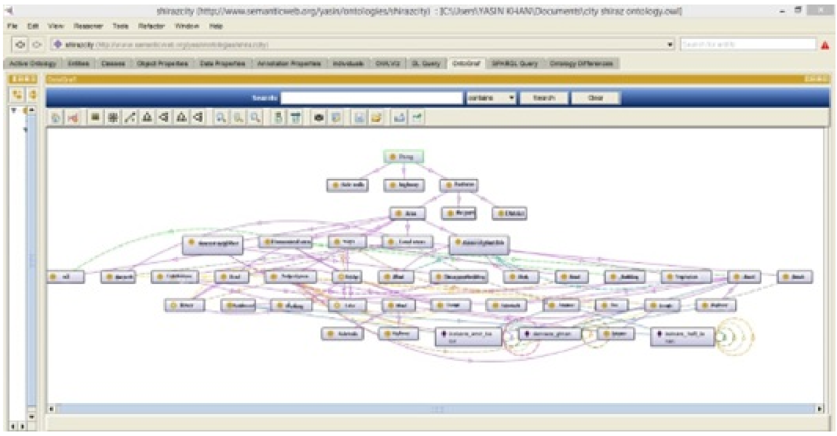


Figure 6: Visually designing the anthology of the city of Shiraz

5 Conclusion

This article demonstrates how SemCityMap can improve search time and enable automatic alternative finding for regions by semantically enriching region representation in ontocity. The framework can be utilized as a tool for better decision making and situational awareness. The article uses Shiraz as an example to showcase various functionalities of SemCityMap.

References

[1] A. Agresta, G. Fattoruso, M. Pollino, F. Pasanisi, C. Tebano, S. De Vito, and G. Di Francia, *An ontology framework for flooding forecasting*, Computational science and its applications–ICCSA 2014, 14th Int. Conf., Guimarães, Portugal, Proc., Part IV, Springer International Publishing, **14** (2014), 417–428.

[2] A. Bashir, R. Nagpal, D. Mehrotra, and M. Bala, *Knowledge representation and information retrieval from ontologies*, R. Kumar, A.K. Verma, T.K. Sharma, O.P. Verma and S. Sharma, (eds) Soft computing: Theories and applications, Lecture Notes in Networks and Systems, Springer, Singapore, **627** (2023).

[3] R.F. Calhau, T.P. Sales, Í. Oliveira, S. Kokkula, L.F. Pires, D. Cameron, G. Guizzardi, and J.P.A. Almeida, *A system core ontology for capability emergence modeling*, Int. Conf. Enterprise Design, Operations, Comput., Cham: Springer Nature Switzerland, 2023, pp. 3–20.

[4] B. Dutta and P.K. Sinha, *An ontological data model to support urban flood disaster response*, J. Inf. Sci. **0** (2023), 01655515231167297.

[5] H. Gu, H. Li, L. Yan, Z. Liu, T. Blaschke, and U. Soergel, *An object-based semantic classification method for high resolution remote sensing imagery using ontology*, Remote Sens. **9** (2017), no. 4, 329.

[6] K. Kalabokidis, N. Athanasis, and M. Vaitis, *OntoFire: an ontology-based geo-portal for wildfires*, Natural Hazards Earth Syst. Sci. **11** (2011), no. 12, 3157–3170.

[7] N. Karthikeyan, I. Gugan, M.S. Kavitha, and S. Karthik, *An effective ontology-based query response model for risk assessment in urban flood disaster management*, J. Intell. Fuzzy Syst. **44** (2023), no. 3, 5163–5178.

[8] M. Längkvist, A. Kiselev, M. Alirezaie, and A. Loutfi, *Classification and segmentation of satellite orthoimagery using convolutional neural networks*, Remote Sens. **8** (2016), no. 4, 329.

[9] A.Y. Lin, S. Arabandi, T. Beale, W.D. Duncan, A. Hicks, W.R. Hogan, M. Jensen, R. Koppel, C. Martínez-Costa, Ø. Nytrø, and J.S. Obeid, *Improving the quality and utility of electronic health record data through ontologies*, Standards **3** (2023), no. 3, 316–340.

[10] M.A. Mostafavi and M. Bakillah, *Real time semantic interoperability in AD HOC networks of geospatial data sources: Challenges, achievements and perspectives*, ISPRS Ann. Photogramm. Remote Sens. Spatial Inf. Sci. **1** (2012), 217–222.

[11] M. Priadarsini and M.K. Dharani, *Distributed inference approach on massive datasets using MapReduce*, Int. Conf. Comp. Commun. Inf., IEEE, 2023, pp. 1–7.

[12] J. Rodríguez-Revello, C. Barba-González, M. Rybinski, and I. Navas-Delgado, *KNIT: Ontology reusability through knowledge graph exploration*, Expert Syst. Appl. **228** (2023), 120239.

[13] R.J. Rovetto, *The ethics of conceptual, ontological, semantic and knowledge modeling*, AI & Society, Springer, 2023, pp. 1–22.

[14] D. Shukla, H.K. Azad, K. Abhishek and S. Shitharth, *Disaster management ontology-an ontological approach to disaster management automation*, Sci. Rep. **13** (2023), no. 1, 8091.

[15] K.J. Sowmiya Narayanan and A. Manimaran, *Recent developments in geographic information systems across different application domains: A review*, Knowledge Inf. Syst. **66** (2024), no. 3, 1523–1547.

[16] X. Xu, Y. Zhong, L. Zhang, and H. Zhang, *Sub-pixel mapping based on a MAP model with multiple shifted hyperspectral imagery*, IEEE J. Selected Topics Appl. Earth Observ. Remote Sens. **6** (2013), no. 2, 580–593.