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Knowledge-based Discovery of Transportation Object Properties by Fusing Multi-modal GIS Data

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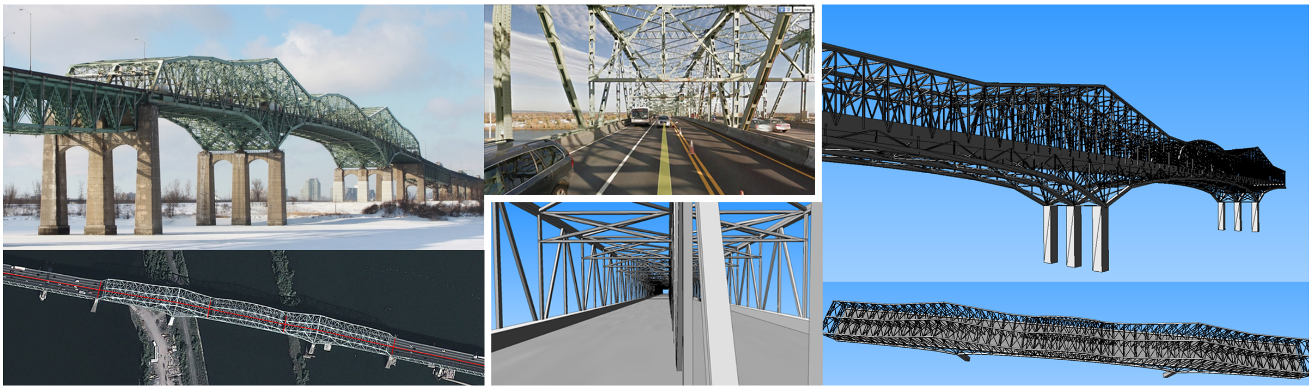

Figure 1: *Detailed reconstruction from GIS data of the Champlain Bridge in Montreal, Canada. Left and middle images are for reference.*

Abstract

3D models of transportation objects like a road, bridge, underpass, etc. are required in many domains including military training, land development, etc. While remote sensed images and LiDaR data can be used to create approximate 3D representations, detailed 3D representations are difficult to create automatically. Instead, interactive tools are used with rather laborious effort. For example, the top commercial interactive model generator we tried required 94 parameters in all for different bridge types. In this paper, we take a different path. We automatically derive these parameter values from GIS (Geographic Information Systems) data, which normally contains detailed information of these objects, but often only implicitly. The framework presented here transforms GIS data into a knowledge base consisting of assertions. Spatial/numeric relations are handled through plug-ins called property extractors whose results get added to the knowledge base, used by a reasoning engine to infer object properties. A number of properties have to be extracted from images, and are dependent on the accuracy of computer vision methods. While a comprehensive property extractor mechanism is work in progress, . a prototype implementation illustrates our framework for bridges with GIS data from the real world. To the best of our knowledge, our framework is the first to integrate knowledge inference and uncertainty for extracting landscape object properties by fusing facts from multi-modal GIS data sources.

CCS Concepts

•***Computing methodologies*** $\rightarrow$ *Computer graphics; Description logics; Reasoning about belief and knowledge ;*

1. Introduction

Creating detailed 3D digital representations for land regions is often a very labor intensive process requiring a human to manually analyze the available Geographic Information Systems (GIS) data and estimate parameter values for use with 3D modeling tools. Terrain, land objects and other components like texture and materials are usually extracted from geospatial databases for a real world region of interest (ROI). Three main components in GIS data are elevation, imagery and geometric features. While, elevation and imagery are easily available as a result of advances in sensing technologies, feature data (also known as vector data) and the associated 3D models are usually not. Often, a transport object such as road, bridge or underpass is represented as just a linear element, i.e., polyline segments with no other identification in-

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formation. In current practice, the best automated representation which one can derive is to use elevation and imagery, and semi-automatically generate a textured mesh of the terrain (ground surface). This is what we often see in systems such as Google Earth®. Objects like bridges will be baked into the terrain rather than show up distinctly in the landscape. 3D detailed representations have to be hand-crafted, typically by using interactive modeling tools, an onerous task requiring considerable expertise and skill.

We present a new knowledge-based framework for discovering object properties from GIS data, significantly extending previous work by Pedro et. al in [EM09]. Important capabilities of our framework are: 1) It fuses information from different GIS data types into a single knowledge base (KB) [BLHL*01] and the property extractors mechanism from [EM13] for handling spatial/numeric relations. The KB consists of assertions with support for associating certainty values. 2) It infers object properties based on specialized domain ontologies. 3) It calculates resulting certainty for inferred properties using the explanation services of the reasoning engine [HPS08] and Fuzzy semantics [Zad65]. 4) It illustrates creation of a complex 3D model of a bridge with properties extracted from the KB. Fig. 1 shows an example of such a 3D model. A significant contribution of this work is the way knowledge-based processes are incorporated into a pipeline framework for discovering object parameters. The framework is illustrated for bridge objects with all their complex structures, but is easily extensible by adding other domain knowledge.

Spatial relationships extend the Dimensionally Extended nine-Intersection Model (DE-9IM) standard [CSE94] to 3D and get added as assertions. A distinguishing feature is our capability to associate a certainty value, ranging from 0 - 1, with the assertion. It can be used to create choices resulting in increased reconstruction accuracy, e.g., a 4 lane bridge with 60% certainty or a 3 lane bridge with 40% certainty. This is described in more detail in Section 4.1.

Completeness of representation is guaranteed by providing default values for every object parameter. Default values may be overridden by extraction or inference, depending on the information present in the input data. Inspite of the limited resolutions in public and free GIS datasets we had access to, we are able to generate 3D models with more detail than what is currently possible, except through human intervention. The expert knowledge that we encoded (transportation domain ontology) as part of our prototype is reusable as it relates to the domain rather than the specific region of interest. The property extractors we have implemented in our prototype use GIS data (e.g. raster, vector, and elevation). These can be used on different resolutions. Values extracted from low resolution data are assigned lesser certainty. This would however be a decision by the plug-in programmer. Inconsistencies, and the explanations provided can be reviewed and decided upon by users.

2. Background and Related Work

In this section, we first summarize work which addresses the use of semantics in GIS applications. Then we review other work which addresses the problem of generating details by inferencing. Third, we describe attempts to formalize object definitions through taxonomies and ontologies. Lastly, we describe how uncertainty has been handled in the semantic Web domain. We end this section by presenting our distinct method of associating certainty values based on explanations provided by the reasoning engine.

2.1. 3D Landscape Rendering

Our closest competitor is Google Earth® and associated tools which can be used to display custom 3D models in maps and terrains. They use prepared satellite imagery and geo-referenced 3D model databases to retrieve information for users' queries. 3D models are created through school competitions or by marketers which are then added to the public database. Best automatic representations usually consist of a baked overpass that seems molten over terrain. Examples in Section 6 illustrate this point clearly.

2.2. Urban Reconstruction

Another closely related area is the field of urban reconstruction in which there has been extensive research using computer vision and graphics techniques applied to remote sensed images and LiDaR data. The primary goal is however different since these techniques concentrate largely on automatic reconstruction of 3D models of buildings/building complexes, and also to some extent street networks. For some comprehensive surveys, we refer the reader to [MWA*13], [BTS*17], [CPP18]. Most techniques are based on hand-crafted features, use colour or LiDaR or both, and obtain the model through an optimization process [KFWM17]. They often have to make certain simplifying assumptions about the two or two and half dimensional nature of buildings, streets and other objects. Since the gathered data could be noisy and could also have missing data, in the last few years, we have also begun to see methods applying deep learning. They carry out semantic labelling at the pixel level in the first step and then do reconstruction by aggregation of pixels into clusters representing objects [ZZ18], [HMP18]. The resulting 3D object models, need considerable post processing (often with manual effort) particularly due to the jaggedness present in object boundaries. There is no major overlap with this work as such, except that we could use these methods in our property extractor mechanism or in a pre-processing step and add the results as suitable facts (with associated certainty) to the knowledge base.

2.3. Semantics in GIS

The Semantic Web [BLHL*01] addresses knowledge representation and interpretation. It allows the definition of formal knowledge in the form of ontologies that cooperate with assertional data and other components within a system. The system forms the knowledge base and normally includes a reasoner engine that delivers answers to semantic queries based on defined semantics such as *SROIQ* [HKS06]. The reasoner engine provides several services including a knowledge base (KB) realization service, which reveals implicit information as well as inconsistencies, if any.

Within the GIS domain, such concepts as ontology-driven geographic information systems and the geospatial Semantic Web have fueled a plethora of research in semantic similarity and knowledge sharing [MDH05]. [WG07] introduced semantic web to automate geospatial data retrieval using a task-based ontology for immediate response personnel. Ordinance Survey, Great Britain's National Mapping Agency is developing an integrated system and ontology to share information consistently between all their systems [Goo05]. [FEAC02] describe the use of ontologies to integrate information in different sources and to determine embedded knowledge for use by client applications. [HTL07] used Semantic Web for detecting types of complex road intersections in image sequences to define and predict movements and restrictions of cars. [VABW09] visualize simulated urban spaces in the future by inferring on gathered data such as the original street network and aerial imagery. A classification of all objects in the visual domain was developed in 2005 [Bit05]; the author mentions that his work has contributed to a 14,000 unique concept taxonomy in the visual objects domain and 1,100 3D models representing some of these concepts. It is publicly available by the name of Visual Objects Taxonomy and Thesaurus (VOTT), however not formally encoded for use in an inference engine. The same author also investigated automatic selection of textures for road signage based on road layouts, generation of vegetation based on statistical input [Bit07], and enhancing scene generation based on the probability of missing elements such as mailboxes next to houses or stop signs at intersections [Bit08]. He did not formulate a process for determining the existence of such objects and admits of a high failure rate in most realistic cases. In the above, individual methods are used for extracting values specific to the problem at hand. We have generalized this into a property extractor mechanism in our framework. [BASR*06] suggests a methodology to develop GIS ontologies as an extension to the Semantic Web mainly for the purpose of geo-referencing documents such as tasks and data. This same methodology is used by us for formalizing definitions of data objects. In [YWR09] and [KCM06], use of ontologies for generating 3D content was mentioned. While the first addresses the generation of building models from architectural drawings, the second uses ontologies to generate graphics content through knowledge-driven visualization.

A GIS to Geometry process was first described in [EM09] and the property extractors framework in [EM13]. The basic framework (based on *SROIQ* semantics) has inspired the framework presented here. However, it differs significantly - firstly by computing object-object relationships with the DE-9IM extensions, it enables much more implicit spatial knowledge to be revealed. Secondly, by managing and computing certainty values for inferences from explanations provided by the reasoner, it can provide multiple options to the end user. Thirdly, we illustrate a complex real world example - a detailed 3D model of the Champlain bridge in Montreal.

2.4. Regarding Uncertainty of Data

Much of the work in the domain of possibilistic logic is described by [Str01]. [Luk08] attempted to use probability theory by defining a concept-concept probability interval association such as a *Bird Flies* with probability between 90-95%, *Bird* has *Wings* with probability over 99-100%, and then answering queries such as “if a *Bird* does not *Fly* what is the probability that it has *Wings*”. These systems model probabilities in the terminology and attempt to represent imprecise concepts. Reasoners such as FuzzyDL [BS11], DeLorean [BDGR12] and Pronto [KP13] are overly complex and inefficient to what is required by our process as they try to address the generic problem of uncertainty in knowledge [Luk08].

In our work, we gain direct access to axioms within the knowledge base and define our own method of dealing with uncertainty basing it on the work of [PSS09] who have advocated the principle of separation of probabilities and meanings. We model uncertainty using Zadeh semantics (described in 4.1) and not probability theory as reasoned below. Consider the following Axiom 1 using description logic (DL) based on Table 1:

Table 1: *SROIQ description logic semantics axiom syntax.*

Constructor	Syntax	Example
Atomic concept	A	Bridge
Individual	a	S253(Champlain)
Top	$\top$	Thing
Bottom	$\bot$	Nothing
Atomic role	r	intersects
Conjunction	$C \sqcap D$	Thoroughfare ⊓ Bridge
Disjunction	$C \sqcup D$	Bridge ⊔ Tunnel
Negation	$\neg C$	¬Bridge
Existential restriction	$\exists r.C$	∃Next_To.Monument
Universal restriction	$\forall r.C$	∀over.WaterBody
Value restriction	$\ni r.\{a\}$	∋under.{S253}
Number restriction	$(\geqslant n R)$ $(\leqslant n R)$	⩾2 Next_To ⩽1 hasBoundingBox
Subsumption	$C \sqsubseteq D$	Bridge ⊑ Thoroughfare
Concept definition	$C \equiv D$	Bridge ≡ ∃Over.WaterBody
Concept assertion	$a : C$	S252 : WaterBody
Role assertion	$(a, b) : R$	(S253, S252) : over

$$\begin{aligned} Tunnel \equiv \exists Through.(NaturalObj. \sqcup Structure) \\ \sqcup \exists Under.(NaturalObj. \sqcup Structure \\ \sqcup Thoroughfare) \end{aligned} \quad (1)$$

Axiom 1 above is a terminology axiom which defines an instance of a "Tunnel" as any entity "through" a natural object or structure or any entity "under" a natural object, a structure or a thoroughfare. The two concepts of $Through$ and $Under$ are mutually exclusive. Let us assume for instance I the probability of occurrence of $Through$ with some $NaturalObj.$ to be 0.5 and that of $Under$ with a different object 0.5 as well. Using probability theory $(P_{A \cup B} = P_A + P_B)$ we have $P(I : Tunnel) = 0.5 + 0.5 = 1.0$ suggesting that this instance is definitely of type $Tunnel$. What we want here is a certainty of 0.5 since either $Through$ or $Under$ are required to classify I as a $Tunnel$. For this reason, we use the Zadeh logic based on [Zad65] (cf Table 2).

Table 2: *Popular fuzzy logics. (after [BS11])*

Family	t-Norm $\alpha \otimes \beta$	t-Conorm $\alpha \oplus \beta$	Negation $\ominus\alpha$	Implication $\alpha \Rightarrow \beta$
Zadeh	$\min\{\alpha, \beta\}$	$\max\{\alpha, \beta\}$	$1 - \alpha$	$\max\{1 - \alpha, \beta\}$
Gödel	$\min\{\alpha, \beta\}$	$\max\{\alpha, \beta\}$	$\begin{cases} 1, & \alpha = 0 \\ 0, & \alpha > 0 \end{cases}$	$\begin{cases} 1, & \alpha \leq \beta \\ \beta, & \alpha > \beta \end{cases}$
Łukasiewicz	$\max\{\alpha + \beta - 1, 0\}$	$\min\{\alpha + \beta, 1\}$	$1 - \alpha$	$\min\{1 - \alpha + \beta, 1\}$
Product	$\alpha \cdot \beta$	$\alpha + \beta - \alpha \cdot \beta$	$\begin{cases} 1, & \alpha = 0 \\ 0, & \alpha > 0 \end{cases}$	$\begin{cases} 1, & \alpha \leq \beta \\ \beta/\alpha, & \alpha > \beta \end{cases}$

2.5. On Extracting Object Properties from GIS Source Data

Fig. 2, based on [EM09], summarizes the various sources of GIS data and how they are currently transformed into a 3D representation. In current practice, landscape object parameters have to be inferred and extracted by the human expert from available digital terrain model (DTM), images and shapefiles [ESR98]. Some commercially available systems such as Presagis' TerraVista and Diamond Visionics' GenesisRT allow a user to define rules by which data present in shapefiles can be converted into generic 3D models chosen from a user-developed model repository. LIDAR data, if available for specific objects, may be used to add further detail to the 3D objects [SD07]. The dashed arrow looping back is indicative of the fact that the human expert may have to iterate a number of times before finalizing the 3D representation and get it all correct.

Fig. 3 illustrates a basic example. Let the shapefile include an area element (a polygon) and one or more records defining a linear element (a polyline) which crosses the area element. These are shown overlayed on the left. The shapefile does not however have information whether the linear element is a road, bridge, underpass, overpass, etc. and also does not have any information about the type of the area element. Assume this area element is recognized by the human expert as water. Then, knowing that the linear element is above the water level (imagery on the right) implicitly makes it a bridge. The widths along different sections can be calculated from the raster image. Clearly, the fact that there is a bridge of certain type and width(s) in this region of interest has been implicitly present in this multi-modal GIS data.

3. Overview

Fig. 4 shows the overall pipeline of our framework. In a preprocessing step, the following are created: (i) A domain ontology (transportation here, with particular attention to bridges), (ii) A source data ontology inherited from the domain ontology to enable mapping from source data to KB for the specific region of interest, (iii) an output data ontology inherited from the domain ontology to

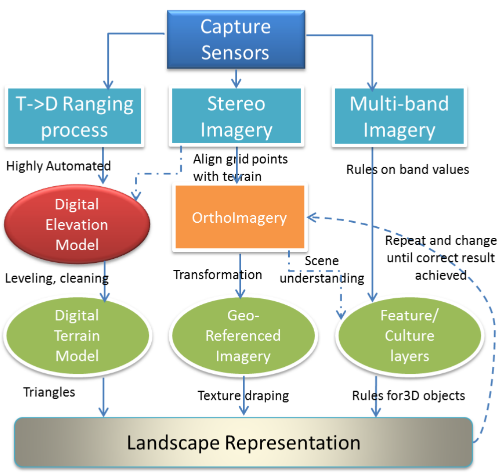


Figure 2: *Current processes used for detailed landscape representations.*

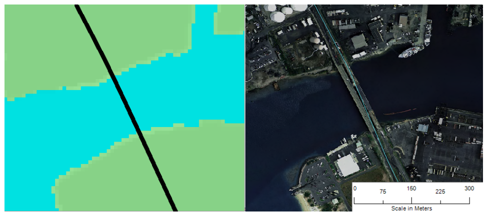


Figure 3: *Shapefile data and imagery of a bridge.*

enable mapping KB to procedural models for generating 3D models of specific instances, and (iv) a 3D repository of parameterized procedural models. These ontologies and resources are available by contacting first author. While we have used the commercially available Presagis Creator®, any other state of the art procedural modeling tool would also work.

Using the source data ontology, the GIS2KB transforms all the information in the GIS data into instance assertions and properties in the KB. For the simple example in Fig. 3, the water area polygon and the thoroughfare polyline are added as instances to the KB. Next, the reasoner engine is invoked to realize the KB and infer information about the instances. This will reveal their specific identities. In our above example, the thoroughfare element is automatically inferred to being a bridge due to it crossing the water area. Using property extractors, values of specific parameters needed are extracted and the KB is realized again. This is repeated until no new information is revealed. For instance, the bridge is identified as a two-lane uncovered bridge. The semantic engine provides knowledge management and reasoner services to its clients, GIS2KB and KB2Scene. KB2Scene uses the representation capabilities ontology to query all object instances and their property values. It then invokes the corresponding procedural model generator. This 3D model is then added to the landscape terrain, an uncovered bridge in this simple example. We will provide further examples in Section 6. The initial setup for a GIS features domain (like transportation) would require expert time in defining the ontologies and the scripting of property extractors. These are reusable for the domain. In the remaining process, significant domain expert involvement is not required. As a fully worked out example, Fig. 1 shows the reconstruction of the complex Champlain bridge in Montreal. More details of the two main processes in this pipeline are provided in the following sections.

4. Transforming GIS Data into Knowledge

The ontologies we define are based on knowledge bases implementing the OWL language [BVHH*05] and the latest OWL 2 specification [W3C12]. Bitters' VOTT [Bit05] organizes elements in the domain of natural and man-made objects. Our domain ontology is also inspired by Bitters' work as a classification basis and implements a subset of VOTT concepts enriched with rules for the purposes of inference. Bitters defines concepts in a plain text taxonomy, like:

- *Street*: Is a Road in a BuiltUpRegion.
- *Boulevard*: Is a broad divided Street in a city often with a wide median, especially a Street laid out with trees and gardens, etc.

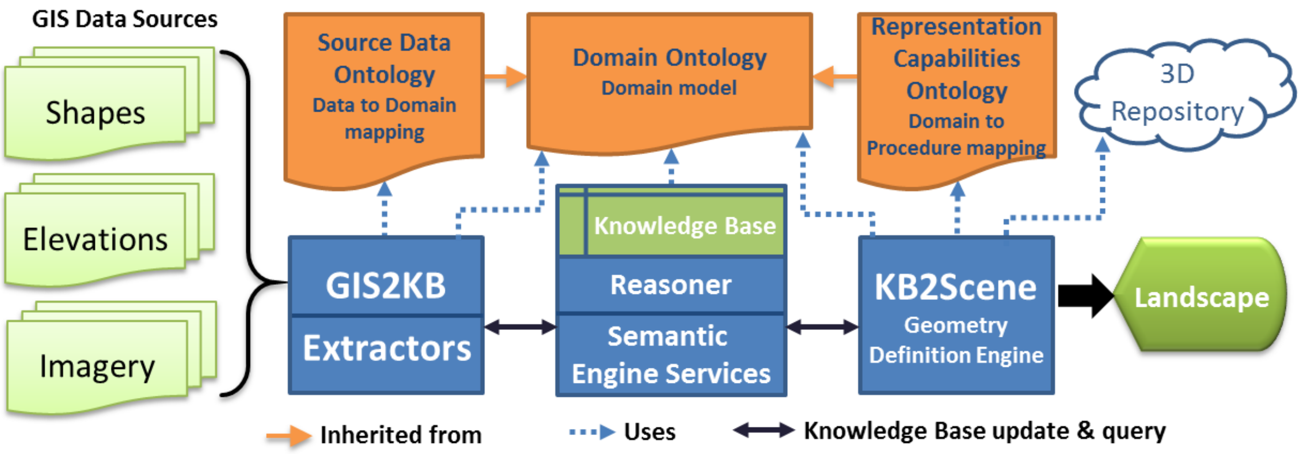


Figure 4: *Schematic of our knowledge-based approach for creating detailed landscapes from GIS data.*

- *Bridge*: Is the subclass of LandTransitways that are artifacts used for crossing water or air-filled gaps that could not be transited over a natural surface.

We define such concepts as Terminology axioms shown below:

$$
\begin{aligned}
Street &\equiv Thoroughfare \sqcap \exists Within.BuiltUpArea \\
Avenue &\equiv Thoroughfare \\
&\quad \sqcap \exists Number\_Of\_Lanes.(xsd:int :\geq 2) \\
&\quad \sqcap \exists_{\geq 1} Touches.(Monument \sqcup Park) \\
Boulevard &\equiv Avenue \\
&\quad \sqcap \exists Midsection.\{\text{“}WideSep\text{”}\hat{}\hat{}xsd:ID\} \\
Bridge &\equiv Thoroughfare \sqcap \exists Over.ImpassableArea
\end{aligned}
$$

We use these axioms where an instance of type *Thoroughfare*, based on the above definitions, could be re-classified as *Avenue* if it has 2 or more lanes and is next to at least 1 monument or park. It should also be noted that *Bridge* inherits properties from *Thoroughfare* such as its *width*, *type*, *lane numbers* and *pavement type* and adds new data properties such as *Deck Thickness* related to this specialization. Domain concepts are encoded once. The input GIS source data however changes for different regions of interest. As required (Fig. 4), three ontologies were created: (1) TD ontology — transportation domain ontology, (done once and reusable for transportation domain in multiple regions of interest) (2) SD ontology — defines mapping between GIS feature data and domain concepts in TD, and (3) RC ontology — performs a mapping between object classes and procedural models in Presagis Creator®.

GIS2KB (based on [EM09]) first maps shapefiles using the SD ontology into KB assertions. Certainty values are associated with these assertions. The KB is realized for the first time using the KB Realization service. If there is an ambiguity or an inconsistency in the input information, the user has to correct this problem. Next, spatial relationships between objects are computed based on the DE-9IM model (See Fig. 5) and the KB is realized again. DE-9IM [CSE94] is an Open Geospatial Consortium standard. It is in the form of a matrix which defines topological relationships between two spatial objects in R^2. We extend this in our framework by adding new 3D relations, allowing. relationships such as *Over*, *Under*, and *Touches* to enrich the knowledge base further.

Property values may also be defined via rules specific to the domain. For example, the height of an overpass has to be a minimum of 4 Meters. Extractors may associate a certainty value with an instance property. All new property values which are extracted are added to the KB, KB realization is repeated, new inferences are obtained and object instances get specialized possibly requiring values for new properties. This KB update loop ends when there are no more changes to KB. Certainties are set to 100% by default.

4.1. Uncertainty Computations

Referring to extractors defined in [EM13], many could be associated with some uncertainty or thresholds such as *PrecedenceByImagery*, *Next_to*, *Impassable_Through*, *Between*, *Thickness*, *Separators*, *Road_Directionality*, *Number_of_Lanes*, etc. Some other extractors such as *Position* (extracts an origin location for an element), *Altitude* (extracts the altitude at a certain location), *OL* (extracts the orientation and length given a linear segment), n (extracts the ground normal at a certain location), N (extracts the average normal given an areal shape), and D (uses *OL* and N to calculate the 3D orientation for an object) as well as spatial relationship extractors which can be defined by formulae are associated with 100% certainty in our implementation. In a conventional knowledge base, if a *roadwidth* extractor for an instance I returns a value 3.2(meters) then we can only assert $((I, \text{“3.2”}) : roadwidth)$ (TRUE). We extend our KB by storing the certainty value c (denoted as $(axiom)(c)$) as part of the knowledge base in the form of an annotation (serving as storage-only for the reasoner). This annotation could in principle be used by probabilistic description logic reasoners such as Pronto (pellet-based). However, these reasoners are computationally prohibitive and our needs are much simpler. We have therefore extended the default

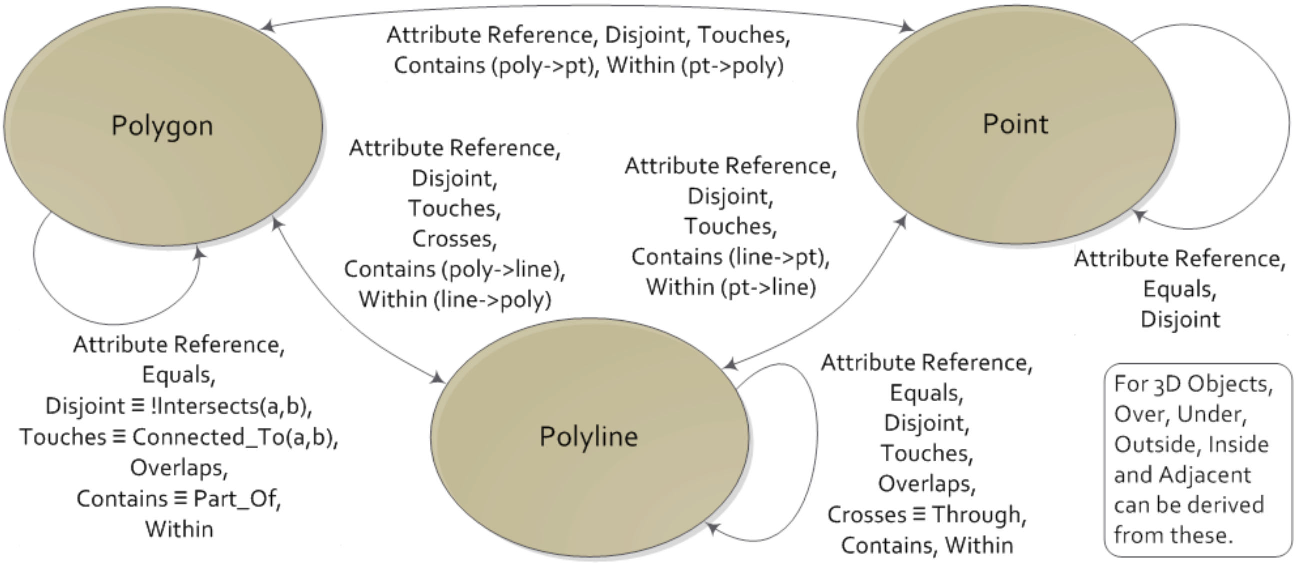


Figure 5: *Object-object relations.*

KB Realization service with a procedure to compute all resulting certainty values using the KB explanation service. To the best of our knowledge, this method of certainty evaluation from inference explanations is new.

According to [HPS08], an explanation for an entailment (E) is a minimum list of axioms that directly results in the entailment. An entailment is the final inferred assertion, say for example, the sequence of assertions which lead us to conclude that a linear element is a tunnel or bridge, etc. For every explanation, the least certain axiom represents the entailment's certainty value under Zadeh semantics. The function $u(x)$ represents the certainty value c of an explicit axiom x in E. inf is a function that takes a set of certainty values and returns the minimum value in the set.

$$\forall x \in E, u(x) \in V \qquad \text{(Equation I)}$$
$$u(E) = inf(V)$$

If two or more explanations exist for a certain entailment, then by Zadeh semantics, the entailment's certainty value is the most certain of the results from each explanation. Consider the following assertions in addition to the definition of *Tunnel* given in Axiom 1 from Section 2.4 and where $(i1 : Thoroughfare)$ is initialized:

$$(i2 : NaturalObj.)(c1) \quad (2) \qquad ((i1,i2) : Under)(c4) \quad (5)$$
$$(i3 : Structure)(c2) \quad (3) \qquad ((i1,i3) : Through)(c5) \quad (6)$$
$$(i4 : Throughfare)(c3) \quad (4) \qquad ((i1,i4) : Under)(c6) \quad (7)$$

After knowledge base realization however, KB entails $\{(i1 : Tunnel)(c7)\}$ and 3 explanations given as follows:

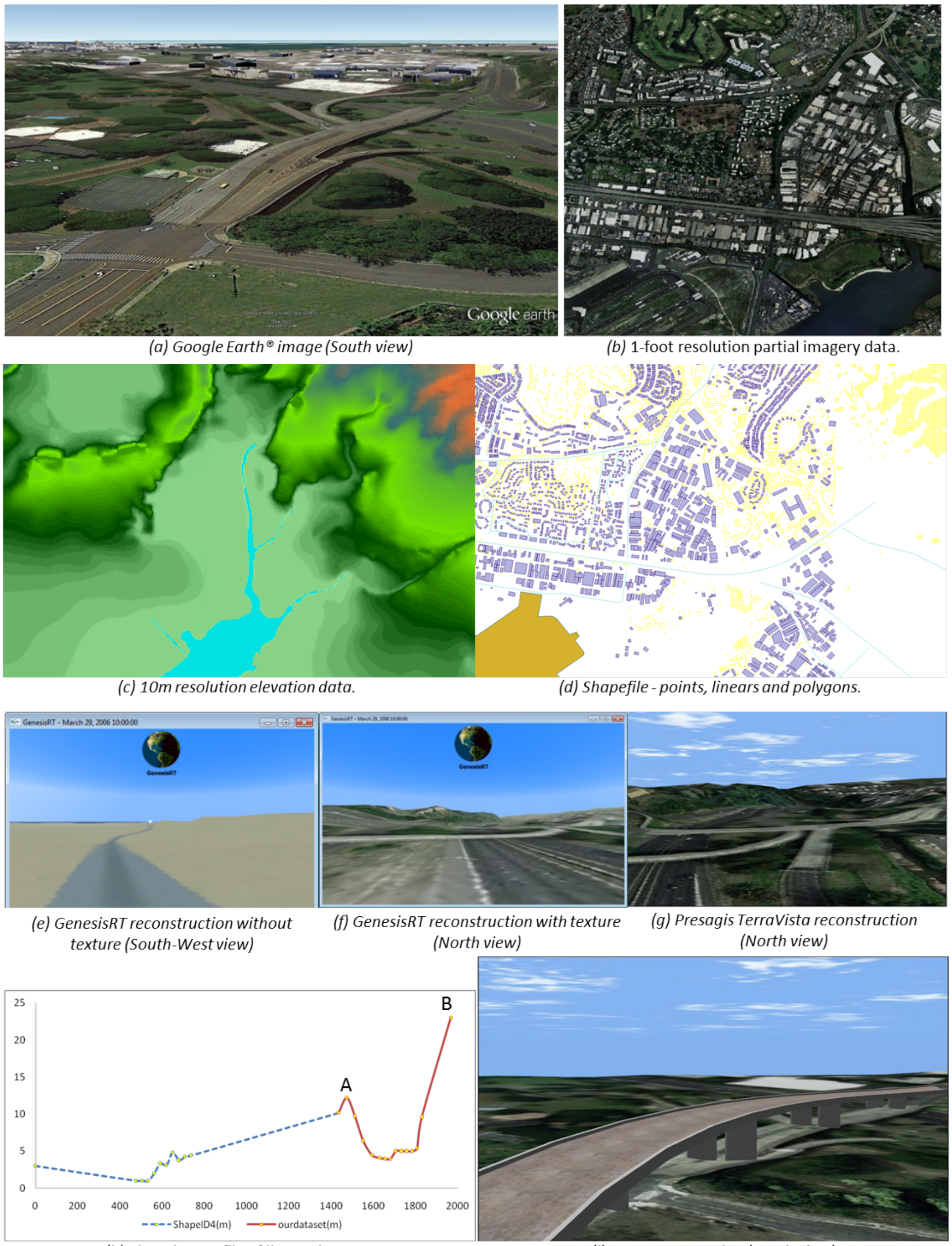
A. (5), (2), (1) B. (6), (3), (1) C. (7), (4), (1)

Explanation A for example, shows that, since instance $i1$ is (spatially) $Under$ instance $i2$ and $i2$ is of type $NaturalObject$, then under 1, $i1$ is entailed to be of type $Tunnel$. Explanations B and C were produced similarly. We discard Axiom 1 from all explanations as we are only interested in assertions concerning the instance $i1$ (separation between probabilities and meanings). If we consider that (2) (3) and (4) are 100% certain facts, then by Equation I the relevant axioms associated with each explanation are simplified to: $((i1,i2) : Under)(c4)$ for (A), $((i1,i3) : Through)(c5)$ for (B), and $((i1,i4) : Under)(c6)$ for (C). The final certainty value is calculated by the disjunction (t-Conorm) of results from each explanation. Therefore, the certainty value for $(i1 : Tunnel)$ is given by $c7 = max(c4, c5, c6)$.

5. Implementation

In this second step, SPARQL queries are used to retrieve instance definitions and property values. Table 3 shows an example of a simple property taxonomy defining three basic classes: *Generic Transport*, *Bridge*, and *Covered Bridge*. Presagis Creator® uses these classes and the listed properties as part of the Bridge Wizard utility. The system fetches each value, produced by property extractors, for every property of *Bridge* as well as its *GenericTransport* super class.

We use the OWL Link specification [LLN*08] and OWL API 3.4.5 as the common API to communicate between the different sub-processes through the reasoner infrastructure and framework. Our system needs the flexibility to be able to add knowledge and extract knowledge from different systems written in different programming languages. It was a challenge to find a feasible solution to allow this. The current systems we use are MapWindow GIS, implemented in C#, the Semantic Web Framework, with most interfaces available only in Java, and our 3D scene generator, implemented in C++. In order to be able to communicate and share knowledge between the different systems for the purposes of proto-



(a) Google Earth® image (South view) (b) 1-foot resolution partial imagery data.
(c) 10m resolution elevation data. (d) Shapefile - points, linears and polygons.
(e) GenesisRT reconstruction without texture (South-West view) (f) GenesisRT reconstruction with texture (North view) (g) Presagis TerraVista reconstruction (North view)
(h) Elevation profile of linear element. (i) Our reconstruction (South view)

Figure 6: *Example reconstruction of a bridge in Honolulu.*

typing and validation, we have created an OWL Link .Net compatible framework based on the original OWL Link Java framework. OWL Link .Net can be used in both C# and C++ programming languages. We have tested the process using Pellet 2.3.1 and Hermit 1.3.8 Semantic Web reasoners. Our ontologies extend public standards from the Open Geospatial Consortium and we obtained data sets from the U.S. Geological Survey's National Elevation Dataset, U.K. Ordnance Survey resources, and Natural Resources Canada GeoGratis system.

6. Results and discussion

6.1. Example 1: A Bridge in Honolulu

- The image shown in Fig. 6 (a) is taken from Google Earth® looking South at (21.348452, -157.896959) geographic coordinates on January 23, 2014. Although a comprehensive visual scene seems to be present, the lack of a 3D model for the bridge is noticeable.
- Elevation raster data, geo-referenced imagery, and linear feature information (from USGS website) are shown in Fig. 6 (b-d), de-

Table 3: *Generic Transport, Bridge and Covered Bridge taxonomy.*

Generic Transport Properties	Bridge Properties	Covered Bridge Properties
Start vertex position	SubClassOf: Generic Transport	SubClassOf: Bridge
Start Angle		
Start width		
End vertex position	Span Dividers	
End Angle	Deck Thickness	Width dividers
End width	Starting vertical angle	Cover Height
Number of segments	Ending vertical angle	Wall angle
Left overhang size	Support width	Entrance angle
Right overhang size	Support depth	
Overhang height		

tailed reconstruction in Fig. 6 (i), and results from two state-of-the-art tools, DVC GenesisRT and Presagis TerraVista in Fig. 6 (e-g). They clearly show the absence of the 3D modeled bridge..

- Based on the elevation profile extractor (results of elevations in meters shown in Fig. 6 (h)), our system inferred that this is a basic uncovered bridge (girder beam bridge between locations A and B of the linear element).

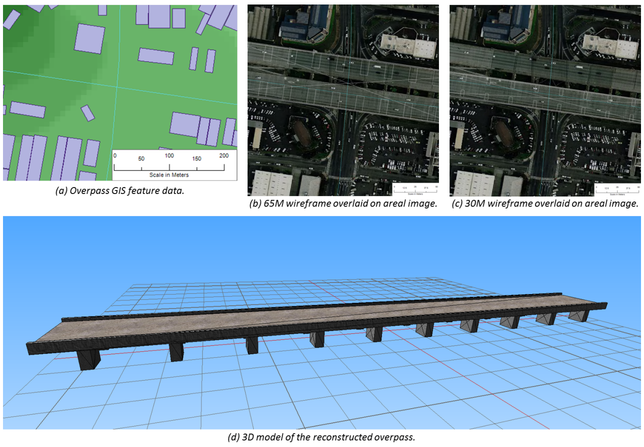


Figure 7: *Overpass in the Honolulu region.*

6.2. Example 2: An Overpass with Multiple Outcomes

- In this example, also in Honolulu, Fig. 7 (a-b), the spatial relationship extractors, based on DE-9IM, define a *Crosses* relationship between the two linear objects.
- Also, the *PrecedenceByImagery* extractor is executed by the *Over* spatial relationship extractor when a *Crosses* relationship exists and no altitude values are available. In this case, the horizontal segment is found to be *Over* the vertical one and therefore an overpass is inferred.
- Based on the results of property extractors, two possible outcomes with widths of 30 and 65 meters with scaled supports are presented. Fig. 7 (b-c) show overlays of the overpass wireframes of the two possible outcomes.
- The extractors fill the necessary property values and the reconstructed overpass object for 30M is shown in Fig. 7 (d).

6.3. Example 3: The Champlain Bridge in Montreal with Multiple Outcomes

Figure 8: *Linear overlaid on Google Earth® Champlain bridge image.*

The Montreal Champlain Bridge is a 1957 construction of type steel truss cantilever made from pre-stressed concrete beams and deck. This bridge is an iconic landmark of Montreal and is interesting due to the complexity of its representation and its art.

- The linear shape definition (a sequence of edges) in the GIS shapefile representing the spans of this bridge is overlaid on top of the aerial imagery (in red in Fig. 8 with four noted locations (cross edges).
- Earlier in Fig. 1 we had already shown this reconstruction with cantilever, support structures, deck and truss of the steel superstructure along with a couple of photographs of the real bridge for comparison. It should be noted that given the unique nature of this bridge, standard repositories in commercial systems do not include the procedural model for accurate reconstruction.

7. Concluding Remarks

The knowledge-based framework presented in this work enables us to create landscape objects with properties discovered from GIS data yielding more automation as compared to purely interactive tools in practice today. It allows customization and can extend legacy processes. Manual work in recurrent tasks is automated by defining domain knowledge and property extractors that are reusable across different datasets. Our method of computing uncertainty of inferences using explanations provided by the reasoner and providing options based on possibilities is innovative and distinct from all earlier work. We have demonstrated our approach by creating models of streets, overpasses and bridges, including the heritage Champlain bridge in Montreal. Other transportation objects can be easily modelled. The framework can take advantage of more accurate extractor algorithms, say, using state of the art computer vision techniques that continue to be developed.

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