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Towards an Ontology for Situation Assessment in Environmental Monitoring

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Abstract: Situation assessment, i.e. the process of achieving situation awareness, is common in environmental monitoring, where assessment occurs predominantly on sensor data and awareness is for the state of environmental phenomena. For a particular location, an environmental monitoring system may measure and compute mean hourly $PM_{2.5}$ concentration to acquire knowledge for situations of unhealthy exposure by humans to ambient air; it may measure aerosol particle size distribution to acquire knowledge for situations of atmospheric new particle formation; it may measure road-pavement vibration to acquire knowledge for traffic. The process can be divided in four generic sub processes, namely data acquisition, data processing, knowledge acquisition and extraction, and knowledge representation and reasoning. We outline an ontology for the process. It aligns and specializes the generic concepts of several upper ontologies. The ontology could form a building block in the discovery and query of situational knowledge acquired and represented by distributed environmental monitoring systems, from heterogeneous sensor data and for diverse environmental phenomena, in time and space.

Keywords: sensor data; knowledge acquisition; knowledge representation; environmental monitoring; situation awareness; wavellite.

1 INTRODUCTION

An environmental sensor network (Hart and Martinez, 2006) is typically deployed to monitor over time, and often over space, one or several properties of environmental phenomena. These systems have had a considerable evolution, from relatively labour intensive “loggers” to wireless sensor networks that automatically forward data to computer systems (Hart and Martinez, 2006). Environmental sensor networks can generate considerable amounts of data. In environmental monitoring, such data is interesting for the information they convey about the monitored environmental phenomena, and the extraction of information can involve considerable processing and several computational methods. Information is situational knowledge and situation assessment is the process (Endsley, 1995).

This process is common in environmental monitoring precisely because it is situational knowledge, rather than data, which is of most interest and value, to both machines and people (Calbimonte et al., 2012; Alirezaie and Loutfi, 2013; Barnaghi et al., 2012). Because it is common and, to the best of our knowledge, little has been done to provide generic software support, the process is implemented often and typically *ad hoc* for a certain domain and purpose. Such implementations are hardly reusable. Even more important, situational knowledge is often not represented explicitly but remains implicit in plots, statistical data, or the unstructured text of scientific manuscripts. Hence, situational knowledge is accessible to humans but not to machines. For instance, air quality experts may analyse time series for $PM_{2.5}$ concentration in air and conclude that over one year there are on average 15 situations of unhealthy exposure lasting 34 hours. Representing knowledge for situations of unhealthy exposure explicitly enables not just the computation of statistical data but also the reuse of knowledge for various other purposes.

Situational knowledge, as understood here, is knowledge (or information) about the physical environment that is monitored in environmental monitoring. Typically, such knowledge is for specific environmental phenomena, such as a group of people, a vehicle, or the particles of an aerosol. However, situational knowledge may also be for non-physical entities, such as a season. For instance, based on the monitoring of temperature we may state the situation of a short 2014 growing season in Finland.

Using five ontologies–namely the Semantic Sensor Network[1] (SSN) ontology (Compton et al., 2012), the RDF Data Cube Vocabulary[2] (QB) (Cyganiak et al., 2013), the Situation Theory Ontology[3] (STO) (Kokar et al., 2009), OWL-Time[4] (Hobbs and Pan, 2006), and GeoSPARQL[5] (Perry and Herring, 2012)–we describe an alignment and extensions that we think can serve as a foundation for an organized and formal vocabulary relevant to the process of interest here. The discussed alignment is the main contribution of this work, is actively maintained, and is available online.[6]

The use of ontologies to represent sensor data and meta data as well as for reasoning on sensor data has gained popularity (Sheth et al., 2008; Compton et al., 2009; Moraru and Mladenić, 2012; Barnaghi et al., 2012; Henson et al., 2009; Stocker et al., 2011). Studies also describe the use of the STO (Fenza et al., 2010; De Maio et al., 2012; Doulaverakis et al., 2011) as well as ontology alignments, e.g., SSN and QB (Lefort et al., 2012). Moreover, various architectures and approaches have been proposed for the extraction of semantic data from sensor data (Gorrepati et al., 2013; Ganz et al., 2013; Calbimonte et al., 2012; Alirezaie and Loutfi, 2013; Barnaghi et al., 2012; Stocker et al., 2014b; Cardell-Oliver and Liu, 2010). However, to the best of our knowledge, we lack of a generic, practical, and complete approach for situational assessment, especially one tailored for environmental monitoring and scientific applications.

2 Process

We divide the process of situation assessment, as understood here, into four generic sub processes, namely data acquisition, data processing, knowledge acquisition and extraction, and knowledge representation and reasoning. In this section we briefly discuss them and highlight the aspects that are relevant to the proposed ontology.

Data acquisition In environmental monitoring, data acquisition is intimately connected to measurement, i.e. the process whereby numbers are assigned to properties of real world objects or events (Finkelstein, 1982, p. 6). Systems for data acquisition are designed for specific properties and techniques. For instance, data for atmospheric temperature may be acquired directly using an instrument installed on a weather balloon or by remote sensing using an instrument installed on a satellite. Each technique has typically some advantages and disadvantages. Today, the numbers resulting from measurement are often digital and managed by computer systems. Moreover, to a particular computer system the source of sensor data is, generally, a system, which may concretely be, among others, a sensing device, a database, a web service, a lab technician, or participatory sensing.

Data processing In preparation for knowledge acquisition and representation, acquired data is often processed in various ways. Generally, data processing is understood as a manipulation or transformation of data. We distinguish between two kinds of data processing. First, processing that resolves the heterogeneity of acquired data by translation into data with homogeneous syntax and semantics. We distinguish the two data types *sensor observation* and *dataset observation*, both with syntax and semantics defined in ontologies. The second kind of data processing operates on dataset observations by processing an input set of dataset observations into an output set of dataset observations. A set of dataset observations is a dataset.

Sensor observations and dataset observations conform to distinct structures. A sensor observation relates to the sensor that made the observation; the feature that is monitored, typically an environmental phenomenon

[1] http://purl.oclc.org/NET/ssnx/ssn
[2] http://purl.org/linked-data/cube
[3] http://vistology.com/ont/2008/STO/STO.owl
[4] http://www.w3.org/2006/time
[5] http://www.opengis.net/ont/geosparql
[6] http://www.uef.fi/en/envi/projects/wavellite/ontologies

such as particulate matter; and the property of the feature that is observed, such as concentration. In addition, a sensor observation relates to the observed value and the time (and possibly space) at which the observation is made. In contrast, a dataset observation relates to a dataset and to a set of component properties. The typical text file with lines of comma separated values can be understood as a dataset, each line being a dataset observation with component property for each value.

With the first kind of data processing, we resolve the typical heterogeneity of acquired data by its translation to sensor observations, which are of homogeneous syntax and semantics. The observations made by a sensor for a certain property and feature form a time series. Such a series can be represented as a dataset, with dataset observations having two component properties, one relating time and the other relating the value of the observed property. Dataset observations can have more dimensions and the values of component properties can be, and mostly are, results of computations while the observation values related to sensor observations are results of sensing (and are considered immutable).

Knowledge acquisition and extraction We distinguish knowledge acquisition and knowledge extraction. The former involves domain experts as the source for ontological knowledge and collaborators in the development of domain ontologies. For instance, domain experts know the temporal extent and concentration level relevant to the modelling of unhealthy exposure to $PM_{2.5}$. In contrast, knowledge extraction is performed by computational agents that implement models. Models rely on computational methods, for instance in machine learning, and may be supervised or unsupervised. Situational knowledge is extracted from dataset observations.

Knowledge representation and reasoning Extracted situational knowledge is represented as situations, with syntax and semantics defined in an ontology grounded in Situation Theory (Barwise and Perry, 1983; Devlin, 1995). For knowledge representation, we rely on Semantic Web (Berners-Lee et al., 2001) technologies, in particular the Resource Description Framework (RDF) (Manola et al., 2004), RDF Schema (RDFS) (Brickley et al., 2004), and the Web Ontology Language (OWL 2) (W3C OWL Working Group, 2012). Generally, knowledge is expressed as a set of statements and RDF is used to encode statements.

Being ontology languages, RDFS and OWL 2 (the latter is more expressive and builds on the former) support the encoding of the semantics of concepts and relations used in statements for situational knowledge. For example, assume a concrete situation of unhealthy exposure to $PM_{2.5}$ lasting 36 hours at a defined spatial location. What is known about this situation can be expressed as a set of statements, e.g. the situation involves $PM_{2.5}$, and we use RDF to do so. These statements include instances of certain domain concepts, e.g. $PM_{2.5}$ is an instance of the concept Particulate Matter, and we use RDFS and OWL 2 to model concepts. Beyond knowledge representation, Semantic Web technologies also support (deductive) reasoning, meaning that, given an ontology describing what is known about situations and the semantics of the vocabulary used, software can automatically infer knowledge that is entailed by (i.e. is implicit to) the ontology.

Situations are formalized by means of the expression $s \models \sigma$, meaning that the infon σ is "made factual" by the situation s. The object $\ll R, a_i, \ldots, a_m, i \gg$ is a well-defined infon if R is an n-place relation and $a_1, \ldots, a_m$ $(m \leq n)$ are objects appropriate for the argument places $i_1, \ldots, i_m$ of R, and if the filling of argument places $i_1, \ldots, i_m$ is sufficient to satisfy the minimality conditions for R, and $i = 0, 1$ is the polarity. Minimality conditions "determine which particular groups of argument roles need to be filled in order to produce an infon" (Devlin, 1995). The polarity is the 'truth value' of the infon. If $i = 1$ then the objects $a_1, \ldots, a_m$ stand in the relation R; else the objects do not stand in the relation R. Parameters, denoted as $\dot{a}$, make reference to arbitrary objects of a given type. For instance, $\dot{l}$ and $\dot{t}$ typically denote parameters for arbitrary objects of type spatial location and temporal location, respectively. Anchors are a mechanism to assign values to parameters. The parameter $\dot{t}$ may anchor the value for the current time. Reasoning occurs on represented situational knowledge and may be performed manually or automatically.

3 Ontology

In environmental monitoring, situational knowledge is typically located in time and space. Hence, in addition to ontologies for sensor observations, dataset observations, and situations we also require ontologies for the modelling of temporal locations and spatial locations. In this section we first briefly describe the relevant upper ontologies before we discuss the proposed ontology alignment and the additional entities we introduced. We generally highlight the most relevant concepts and relations.

Upper ontologies We use OWL-Time and GeoSPARQL to model temporal locations and spatial locations, respectively. OWL-Time defines the class `TemporalEntity` and its subclasses `Instant` and `Interval`. It also defines the two object properties `hasBeginning` and `hasEnd` which relate a temporal entity with an instant. Finally, it defines the data property `inXSDDateTime` which relates an instant with a literal of type `dateTime` (XML Schema data type). Beyond these most relevant concepts and relations, OWL-Time allows for the explicit representation of temporal descriptions (e.g. durations) and topological relations (e.g. before). GeoSPARQL defines the class `SpatialObject` and its subclasses `Feature` and `Geometry`. It also defines the object property `hasGeometry` which relates a feature with a geometry. Finally, it defines the data property `asWKT` which relates a geometry with a literal of type `wktLiteral` (a GeoSPARQL data type) to allow for text representation of geometries. Beyond these most relevant concepts and relations, GeoSPARQL supports the explicit representation of topological relations.

We use the Semantic Sensor Network (SSN) ontology to model sensor observations. The SSN ontology extends the DOLCE+DnS Ultralite[7] (DUL) ontology, which is a simplification of the DOLCE (Masolo et al., 2002) and Descriptions and Situations (DnS) (Gangemi and Mika, 2003) ontologies. The SSN ontology defines the key concepts and relations required to model sensor networks and their observations. Most relevant here are the concepts `Observation`, `Sensor`, `Property`, and `FeatureOfInterest` as well as the object properties that relate an observation with what made it, for which property and feature, as well as when and where it was made.

We use the RDF Data Cube Vocabulary (QB) to model dataset observations. The QB vocabulary defines the key concepts and relations required to model datasets. Most relevant here are the concepts `Observation`, `DataSet`, and `ComponentProperty` as well as the object property `dataSet` which relates an observation to a dataset. `ComponentProperty` is the class of all (RDF) properties that relate observations to component property values. Assuming a typical dataset of comma separated values, we may model the rows as observations and the columns as component properties. Temporal locations, spatial locations, numbers, or text can be represented as values of component properties.

We use the Situation Theory Ontology (STO) to model situations. STO closely follows the semantics of the Situation Theory briefly presented in Section 2. Of particular interest are the concepts `Situation`, `ElementaryInfon`, `Relation`, `Individual`, `Attribute`, `Value`, and `Polarity`. These concepts are clearly reflected in situations $s \models \ll R, a_i, \ldots, a_m, i \gg$ and individuals, attributes, and values may fill positions $a_i, \ldots, a_m$.

Ontology alignment Given that the SSN ontology extends the DUL ontology, we pursue the approach whereby the DUL ontology acts as the 'top' upper ontology, defining the most abstract terminology. We, thus, need to align OWL-Time, GeoSPARQL, QB, and STO with the DUL ontology. According to the DUL ontology, DUL `Entity` includes anything real, possible, or imaginary. Clearly, OWL-Time temporal entities, GeoSPARQL spatial objects, QB observations, datasets, and component properties, as well as STO situations are all DUL entities. Hence, these classes fall within the DUL class hierarchy. The DUL ontology specializes entities in four classes of most interest here, namely `Abstract`, `Object`, `Event`, and `InformationEntity`. We align the classes of other upper ontologies used here into this class hierarchy.

OWL-Time temporal entities are modelled as DUL abstracts, specifically DUL time intervals, which, according to DUL are regions in a dimensional space that aim at representing time. GeoSPARQL spatial objects are modelled as DUL entities, not as DUL objects (which are disjoint with DUL events), because the class GeoSPARQL `Feature` (subclass of `SpatialObject`) is equivalent to the class SSN `FeatureOfInterest` which includes both DUL objects and DUL events. GeoSPARQL geometries are modelled as DUL space regions, i.e. regions in a dimensional space used to localize an entity. QB datasets and observations are modelled as DUL information objects (i.e. DUL social objects). QB component properties are DUL social attributes, i.e. regions in a dimensional space that are used to represent the characteristics of social objects. Specifically, QB component properties are statistical attributes over a collection of QB observations. STO objects are modelled as DUL entities in order not to restrict the objects allowed in infons, which may thus be

[7] http://www.loa-cnr.it/ontologies/DUL.owl

DUL abstract, e.g. a temporal entity, or DUL object, e.g. an STO individual. Moreover, we model STO elementary infons as DUL information objects. We state that SSN sensors, properties, and features of interest are STO individuals. Hence, sensors, properties, and features can be objects in infons. We also specify that SSN observations, QB observations, and STO situations are mutually disjoint classes.

In addition, we align object and data properties of the upper ontologies with the DUL ontology. For instance the GeoSPARQL `hasGeometry` object property is modelled as a sub property of DUL `hasRegion`, which relates DUL entities with DUL regions. Some OWL-Time topological relations that relate temporal entities, e.g. `after`, are also modelled as sub properties of DUL `hasRegion`. Other OWL-Time topological relations, e.g. `intervalOverlaps`, are modelled as sub property of DUL `overlaps`. Similarly, some GeoSPARQL topological relations, e.g. `sfContains`, are modelled as sub properties of DUL `hasPart`. Other GeoSPARQL topological relations, e.g. `sfOverlaps`, are modelled as sub properties of DUL `overlaps`. As for data properties, most are sub properties of DUL `hasRegionDataValue`, which relates DUL regions with a literal. An example is OWL-Time `inXSDDateTime` which relates OWL-Time instants with literals of `dateTime` data type. Another example is GeoSPARQL `asWKT` which relates GeoSPARQL geometries with literals of `wktLiteral` data type. A notable exception is STO `attributeValue` which relates STO values with their literal representation. STO values are not strictly sub classes of DUL regions. Hence, STO `attributeValue` is not modelled as a sub property of DUL `hasRegionDataValue`.

Additional entities In order to distinguish the term `Observation` used in both the SSN ontology and the QB vocabulary, we introduce the terms `SensorObservation` and `DatasetObservation`, which are equivalent classes with SSN `Observation` and QB `Observation`, respectively. This addition is not strictly necessary because the term `Observation` is defined by the SSN ontology and the QB vocabulary in distinct name spaces. However, the explicit distinction of the term `Observation` into `SensorObservation` and `DatasetObservation` is practically useful, for instance in communication.

Inspired by the terminology used by Devlin (1995), we introduce the term `SpatialLocation` modelled as sub class of GeoSPARQL `Feature` and sub class of the STO `Location` attribute. Thus, spatial locations can be used in situations. For instance, a thunderstorm, individual in a situation, has a spatial extent, modelled as a spatial location. We explicitly distinguish spatial locations as `SpatialPlace` or `SpatialRegion`. Spatial places are modelled as DUL places, i.e. DUL social objects. An example for a spatial place is 'the city of Helsinki'. Spatial regions are modelled as DUL physical places, i.e. DUL physical objects, and must relate to a GeoSPARQL `Geometry`. An example for a spatial region is the region delimited by the polygon corresponding to the geographic boundaries of Finland. Equally inspired by the terminology used by Devlin (1995), we introduce the term `TemporalLocation` modelled as sub class of OWL-Time `TemporalEntity` and sub class of the STO `Time` attribute. Thus, temporal locations can be used in situations. For instance, a situation involving a thunderstorm in the city of Helsinki is true (infon polarity) for a temporal location. Akin to spatial locations, we explicitly distinguish temporal locations as `TimePoint` and `TimeInterval` which are equivalent classes with OWL-Time `Instant` and `Interval`, respectively. Naturally, temporal and spatial locations can be used also in sensor observations and dataset observations.

Lacking an appropriate SSN or DUL object property to relate sensor observations with spatial locations, we introduce the `observationResultLocation` object property (akin to SSN `observationResultTime`). DUL `hasLocation` is designed for 'relative localizations'. Hence, we could use this property to relate observations with spatial places. In contrast, SSN `hasValue` (sub property of DUL `hasRegion`) is designed for 'absolute localisations'. However, spatial regions are not DUL regions. Hence, SSN `hasValue` (or DUL `hasRegion`) cannot be used to relate observations with spatial regions. Therefore we introduce `observationResultLocation` to specifically relate sensor observations with spatial locations.

4 Discussion and Conclusion

We argued that the process of situation assessment, understood here as situational knowledge acquisition and representation from sensor data for environmental phenomena, can be divided in four generic sub processes, namely data acquisition, data processing, knowledge acquisition and extraction, and knowledge representation and reasoning. We think that the upper ontologies, their alignment, and our additions described in Section 3 form an ontological framework that is sufficiently expressive to model the results of these sub processes and, thus, the results of the process. Specifically, the result of data acquisition is sensor observations; the result of data processing is dataset observations; the result of knowledge extraction, representation and reasoning, is situations. Critically for environmental monitoring, the ontological framework supports the spatio-temporal localization of sensors, sensor observations, and situations as well as the use of spatial and temporal locations as component property values of dataset observations. Finally, the ontological framework can accommodate knowledge acquired from domain experts for sensors and monitored properties and features, the structure definition of datasets, and the parametrization of situations.

Endsley (1995) distinguishes situation *awareness* and situation *assessment*, the former being “a state of knowledge” and the latter being “the process of achieving, acquiring, or maintaining” situation awareness. With focus on environmental monitoring, we think that the ontological framework proposed here can be used to model situation awareness, more accurately the state of knowledge that *can* be expressed using the chosen modelling languages, as well as to model situation assessment, in particular the results of the process.

The described ontological framework is part of the Wavellite[8] (Stocker et al., 2014a, b) modelling and software framework for situation awareness in environmental monitoring. The ontologies are briefly described and linked at the project page.[9] We can extend the presented ontological framework to include concepts for the computational agents (e.g. situation engine or learning module) that form the Wavellite software architecture. Such an extension could support the ontology-driven configuration of Wavellite applications. Furthermore, Wavellite applications may extend the presented ontological framework with other ontologies (e.g. for the modelling of units of measure) as well as with domain knowledge. We think that the presented ontological framework can be of broader interest, beyond its use in Wavellite. In fact, it proposes a general terminology for situation assessment, which is an important process in environmental monitoring as sensor data is processed to information.

In order to make sure that the alignment and additions are consistent, we have implemented several consistency tests using the OWLAPI (Horridge and Bechhofer, 2009) and the HermiT OWL reasoner (Shearer et al., 2008). Each test consists of minimal ontologies including the aligned schema and instances for temporal locations, spatial locations, sensor observations, dataset observations, or situations as well as combinations thereof.

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[8] http://www.uef.fi/en/envi/projects/wavellite
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