A Place and Event Based Context Model for Environmental Monitoring

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Abstract. The importance of context awareness in support of computational services has been well recognized with applications in areas such as real-time location-based services, dynamic social network collaboration, situational health monitoring, indoor navigation, and the Internet of Things among others. The role of context in these services is generally to support more responsive service delivery for human users or agents. The focus of this paper is a context model for environmental observations, where knowledge of spatial and temporal contextual differences among observations is important for interpretation and analyses as well as facilitating sharing and reuse of data outside the original collection context. This paper builds on the OBOE ontology for observation data and expands spatial and temporal context settings through additional ontologies that support flexible spatial contextual consruction in terms of places and relationships among places and temporal contextual construction in terms of events and event relationships. The goal is to capture spatial and temporal contexts for observations to support machine as well as human interpretation and analysis.

Keywords: spatial-temporal context, ontology based context model, gazetteer

1 Introduction

Context awareness is employed to support intelligent decisions and automate responses to situations and events that have occurred. Context awareness is important for customizing information services in ways appropriate to users' characteristics, devices, spatial and temporal settings, and activities. Many context dependent services have been investigated including location based services, social media, driver assistance services, indoor navigation, and health care situation monitoring [1]. These applications have tended to focus on personalization and adaptability of services to user contexts. An area in which context is also very important but has received less attention is in the provision of context for scientific observations [2]. Environmental observations

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are inevitably influenced by their spatial and temporal settings which could be more explicitly modeled for improved scientific interpretation and analysis of the data.

Contextual information for observation data is often only implicitly available through database schema labels, from plotting locations on a map, or through natural-language based metadata. Observation metadata may include location and time stamps as well as information about the observer and observation protocols. A GPS coordinate location is easy to collect and frequently serves as the reported location of an observation, but a coordinate alone offers little to no information about a spatial setting. Similarly a time stamp locates an observation in time but offers little in the way of temporal context for an observation. For example, water samples taken for water quality assessment may have different spatial settings such as near a point source, at the outlet of a particular stream, or in an urban versus a rural setting. Similarly, water samples have very different temporal context if taken before, during or after a precipitation event. While water quality experts are well aware of contextual related influences on water quality parameters, such context information is typically not explicitly captured in formats conducive for automated search and analysis.

What constitutes spatial and temporal context can be difficult to define and bound, and thus some flexibility and vagueness in specifying spatial and temporal context is desirable. This paper expands on previous work and the OBOE ontology for observation data [3] and explores the use of places, place to place relationships, events and event relationships as building blocks for an open ended spatial and temporal context model. Places are understood to refer to named instances of regions or features [4]. They need not have explicit spatial bounds or alternatively they may have many possible spatial representations. A gazetteer that models places and which is enhanced to model relationships among places is proposed as the basis for flexible spatial context model. Similarly, events and relationships among events provide the basis for temporal context development. Section 2 of the paper reviews previous work on concepts of context and context models. Section 3 presents the proposed place and event based spatial-temporal context model for observations. Section 4 illustrates the proposed observation context model for a specific environmental monitoring setting and Section 5 concludes with some issues for future research.

2 Review of Context and Context Models

Many definitions of context exist. Dey [5] defined context as any information used to characterize the situation of an entity where an entity could be a person, location, object, or event. Context in location based services, for example, typically identifies user location (an X,Y coordinate), an approximate neighborhood, who the user is with, and what activities they are engaged in. Context in wireless sensor networks (WSN) has been defined to include sensor node resources, network characteristics, network states, and energy management [6]. Context is also seen as having scale or different levels of detail encompassing local or fine to large and coarse scales or granularities [6]. One of the complexities of context is its own context dependencies, and a challenging issue is managing the dynamics of context which in a worst case may be in constant flux [7,8].

A context model has been described as a structure for the representation of situations in the real world for interpretation and exchange by machines. Context models specify the entities and relations among entities needed to characterize a situation or setting and have included representation as key-value pairs [5], object-role models [9], and spatial models [10,11,12].

Ontology based context models have been recently introduced to improve interoperability, reusability, and context based reasoning [9], [13, 14]. Several ontology based context models include similar context classes and entities. Becker and Nicklas [15] identify primary context as including identity of entities, location, and time, and most context models include these as high level classes [14], [16]. Becker and Nicklas [15] also characterize four primary ways in which context can be utilized. This paper focuses on context based tagging, the tagging of information to context to allow later action based on this context.

The development of context models has gone hand in hand with substantial growth in new sources of context information. New technologies, including smart phones, smart devices, and sensor networks serve as both consumers and providers of context information. A number of recent context models assume a sensor based information gathering layer where information from sensor streams is analyzed for recognized activities or events [16]. Data acquired from sensors is then used directly as low level contextual information or to reason and construct higher level contextual constructs through inference.

Ontology based context models typically specify a set of general context entities and relations [16], [18,19] and common to many of these is an explicit place or location class. The COMANTO context ontology [15] includes a Place class for representing an abstract or physical spatial region and also includes spatial relationships among places, such as adjacent to, included in, or a hierarchical place containment structure (e.g. cities containing buildings and streets). Temporal context has received a similar level of attention. A number of temporal models rely on events to represent conditions of interest or changes of state. Barreneachea et al [8] describe a distributed event-based system (DEBS) that employs loosely coupled components communicating via event-based asynchronous interactions. Andrienko et al [20] describe spatio-temporal context for movement data that links movement events through spatial and temporal relationships to other locations and events. Janowicz et al [21] emphasize the importance of space and time as contextual foundations in the Linked Data world.

Bowers et al [3] provide an ontology based model for scientific observation data including context specification. They define context as the meaningful surroundings of an observation, including other observations, their measured values, and their relationship to the observed entity. The OBOE ontology [2], illustrated in Figure 1, represents observations as assertions about entities, including one or more measurements, which assign a value to a characteristic of an entity. The OBOE ontology specifies context as a unary relation, hasContext, between observations. A context thus consists of named relationships between one observation and others indicating that an observation has been made within the scope of associated observations [3]. An example from [3] is a measure of diameter at breast height (DBH) as an observation on a tree. This observation is related by a "within" relation to a temporal observation measured in years and by another "within" relation to an observation of a plot as a location measured on a nominal scale.

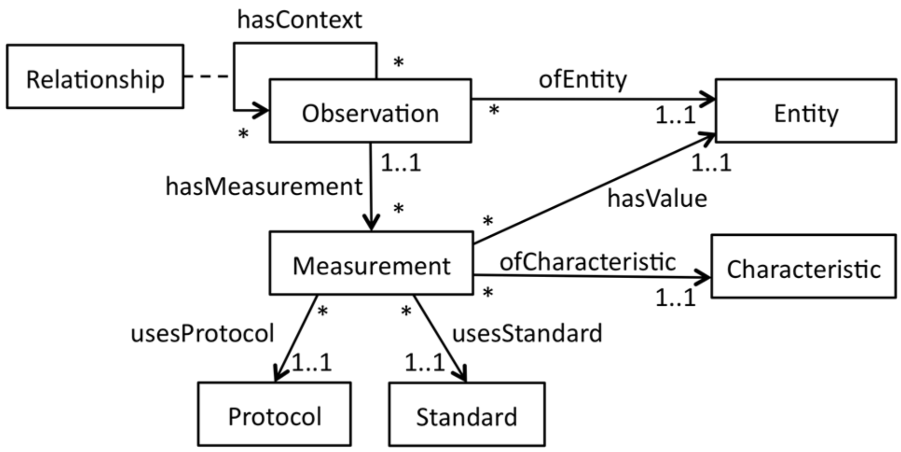

Fig. 1. The OBOE ontology for ecological observation data [3]

This is a flexible model in that any number and type of observation can be associated to create context. A limitation, however, is that no explicit classes of context are distinguished as in other context models [13], [15]. Specifically spatial and temporal context observations are not distinguished from any other context observations and are thus not searchable or retrievable as context components.

A second limitation of the OBOE context model is that it does not support higher level constructs. Context remains a Tier 2 level observable reality in Frank's [22] terms, rather than supporting higher level abstractions over observations. For example Bowers et al [3] give an air temperature observation as a context observation for a tree observation. A single air temperature observation or a daily average provides some level of context, but a sequence of observations abstracted as an event and indicating a period of rising or falling air temperature including the rate of rise or fall provides a higher level and richer context than a single observation.

3 Place and Event Based Context Model for Observation Data

The proposed context model builds on the OBOE and other context models with three objectives: 1) to make spatial and spatio-temporal context distinct (from other types of context), 2) to allow higher level constructs for creating context, and 3) allowing context to be indefinite, open ended, and context dependent. The approach reuses classes and relationships from OBOE including the Observation, Entity, Measurement, and Characteristic classes. In addition it utilizes the hasSpatialSetting and hasTemporalSetting relationships from the GEM model [23], the SpatialObject class from GeoSPARQL [24] and the TemporalEntity class from Owl-Time [25]. Semantic web technologies are used to implement the context model. An ontology based gazetteer implemented as an RDF triplestore supports spatial context construction and provides some level of reasoning over context information. The context model can be queried through SPARQL and GeoSPARQL.

3.1 The Spatial Context Model

The approach for making spatial context explicit and open-ended is managed by assigning an observation a spatial setting and then allowing the spatial setting to be expanded as appropriate. The assigned spatial setting is considered a local spatial context. An OBOE Observation is related to a GeoSPARQL SpatialObject with the hasSpatialSetting property from GEM as shown in Figure 2. The GeoSPARQL SpatialObject class has two subclasses: Feature and Geometry where Feature can be a distinct physical object in the landscape and may refer to a named geographic location or place [24].

Fig. 2. The OBOE observation class is connected through an OWL object property GEM:hasSpatialSetting to a GeoSPARQL SpatialObject class which can be a feature (place) or geometry.

The GeoSPARQL geometry class includes subclasses point, polyline, and polygon among others. The spatial setting for an observation can thus be a named place (feature), a geometry, or both. The GeoSPARQL ontology [24] defines an OWL object property, hasGeometry, between Feature and Geometry classes allowing a feature to be associated with zero or many geometries. A benefit of this approach is that a spatial setting need not imply any specific geometry allowing for some vagueness in the spatial setting. For example one might want to indicate that the setting of an observation is the mouth of a stream without having to specify such a setting with explicit geometry.

The assigned spatial setting can be extended along two possible pathways allowing for open ended context construction. If the assigned spatial setting is a geometry type it can be expanded through spatial relationships [26, 27] among geometry types as supported by GeoSPARQL. For example if the spatial setting of an observation is a polygon representing a field plot, a possible expanded spatial context could be the set of adjacent field plots. If the spatial setting is a place or feature type with no geometry and we wish to expand spatial context we need a mechanism to establish relationships between features. Here we focus on this second pathway as an important way to capture relationships among features or places not easily captured by spatial topological, distance, or directional relationships. This second expansion pathway relies on a semantically enhanced gazetteer that incorporates feature to feature and feature part-whole relationships. The enhanced gazetteer is developed from two ontologies: a geographic feature ontology and a gazetteer ontology. The approach has similarities to the SPIRIT project [28] which defined a three part ontology based model for geospatial search and in follow on work, [29] demonstrated expansion of place name search using spatial relationships such as near, north, south, east, or west of a place name.

The geographic feature ontology models prototypical features (places) and relationships among them. We illustrate the approach for a subdomain of hydrologic features modeled as subclasses of the GeoSPARQL Feature class. A class hierarchy of prototypical surface hydrology feature types is shown in Figure 3. FreshwaterBay and MarineBay are examples of prototypical feature parts. Namespace prefixes used in this example and elsewhere in the paper include geo: GeoSPARQL, hfo: HydrologicFeatureOntology, hgaz: HydrologicFeatureGazetteer.

Specification of feature to feature relationships is the important element that allows a feature or placed based spatial setting to be expanded to a broader spatial context. Specification of these as OWL properties makes use of OWL semantics to support context expansion through inference. The HFO includes OWL object properties; hasHydrologicRelation, hydrologicPartOf and its inverse, hasHydrologicPart, to express general associations between hydrologic feature classes. These general hydrologic relations are specialized by sub-properties (shown in Table 1) to express semantic feature-feature and feature-part relationships between the prototypical hydrologic feature classes. These feature-feature and feature-part relationships are instantiated in a hydrological feature gazetteer. These relationships are initially derived by GIS analysis but once instantiated in the gazetteer triple store they are easily accessed for context expansion without expensive spatial operations.

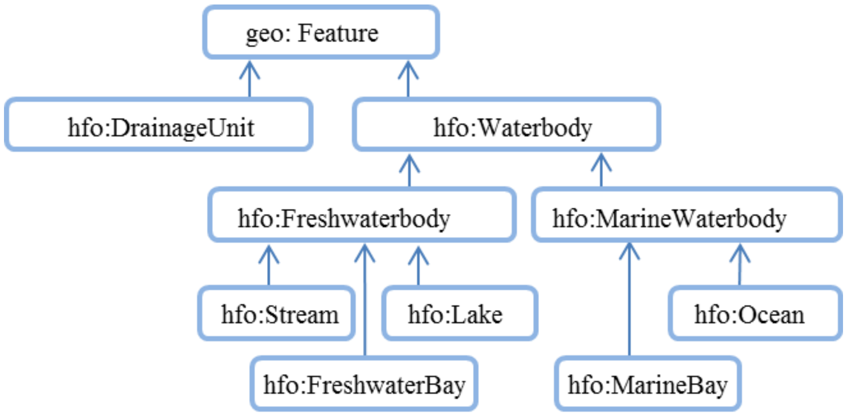

Fig. 3. Class hierarchy of prototypical hydrological feature types.

Table 1. Example OWL object properties, sub-properties and characteristics as specified in the HFO.

Property	SubProperty	Characteristics
hasHydrologicRelation	flowsInto	Antisymmetric, Intransitive
	flowsFrom	
	flowThrough	
	hasInflow	
	hasOutflow	
	isSourceOf	
	hasSource	
	hasMouth	
	isMouthOf	
	isTributaryOf	Antisymmetric, Transitive
	hasTributary	
hasHydrologicPart	hasFreshwater-Bay	Antisymmetric, Transitive
	hasMarineBay	
hydrologicPartOf	FreshwaterBayOf	
	MarineBayOf	

Expansion of a place or feature based spatial setting is executed through queries to the gazetteer triplestore. Table 2 illustrates a SPARQL query template for expanding a feature based spatial setting. Through the SPARQL query, Maquoit Bay, an instance of a MarineBay is expanded to the set of feature instances hydrologically connected to Maquoit Bay. This set of feature instances and their relationships to the spatial setting feature form one possible spatial context. OWL semantics on these relationships such as the transitive property of hasTributary allows the relationships to be expanded to their transitive closure. Thus by inference a connected network of features can be obtained including tributaries of streams connected to Maquoit Bay, bodies of water they may flow through, and drainage units drained by the streams. The standard set of topological, directional, and proximity relationships would not as easily or directly obtain such a set of connected features and parts.

Table 2. SPARQL query template for constructing spatial context through feature to feature relations. The query starts from a named feature (e.g. Maquoit Bay) specified as the SpatialSetting and expands to semantically related features.

```
SELECT ?feature2 ?name2 ?hydrorel,
WHERE {
?feature1   hgaz: gnisname   "Maquoit Bay".
?feature1   rdf:type   ?fclass.
?hydrorel   rdfs:subPropertyOf   hfo:hasHydrographicRelation.  (gets specialized relationships)
?hydrorel   rdfs:range   ?fclass.                 (gets relationships specific to Maquiot Bay's
feature class)
?feature2   ?hydrorel   ?feature1.                (gets the related features)
?feature2   hgaz:gnisName  name2}                 (gets the related feature name)

SELECT ?hydrorel, ?feature2 ?name2
WHERE {
?feature1   hgaz: gnisname   "Maquoit Bay".
?feature1   rdf:type   ?fclass.
?hydrorel   rdfs:subPropertyOf   hfo:hasHydrographicRelation.  (gets specialized relationships)
?hydrorel   rdfs:domain  ?fclass.
?feature1   ?hydrorel   ?feature2.                (gets the features involved in the relationship)

?feature2   hgaz:gnisName ?name2}
```

3.2 Creating Temporal Context

Context in the OBOE model relies on relationships to individual observations and as a consequence misses important aspects of the temporal dimension. Parallel to the spatial context approach, we start with the specification of a temporal setting and allow this temporal setting to be expanded dynamically as needed by identifying events that are temporally related to the temporal setting.

A temporal setting is specified by connecting the OBOE observation class through the object property, hasTemporalSetting to the OWL-Time TemporalEntity class as illustrated in Figure 4. The OWL TemporalEntity has two subclasses, Instant and Interval, which allows a temporal setting to be either an instant or an interval.

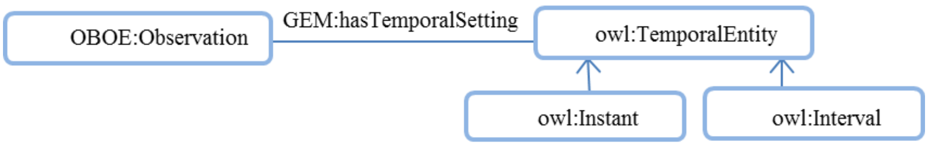

Fig. 4. An OBOE: observation class is connected through the GEM:hasTemporalSetting object property to the OWL-Time TemporalEntity class.

By specifying a temporal setting as a TemporalEntity, we make use of the semantics of OWL-Time. OWL-Time specifies a ProperInterval as a subclass of Interval. A ProperInterval is related to two Instants that specify a start time and end time through hasBeginning and hasEnd object properties. Temporal relationships as specified by Allen [30] can be asserted between ProperIntervals.

A number of context models rely on sensor data for context and context awareness and many rely on events abstracted from sensor data streams [14], [16]. For temporal context expansion we rely on an event database including events obtained as abstractions from sensor time series data. Such events are defined as subsequences of a sensor time series for which a particular property holds over a temporal interval [31]. For example, events extracted from a sensor time series of stream flow based on some domain defined threshold might include BaseFlow, HighFlow, and LowFlow events. Events from other sources, such as generated by human observation, or action (e.g. house construction), can also contribute to temporal context. Events are specified as a subclass of TemporalEntity which means they can be intervals or instants. Events are also assumed to have spatial settings, here specified by the GEM: hasSpatialSetting property to the GeoSPARQL SpatialObject class. Thus similar to an observation, an event can be situated in a place (feature) or by geometry (point, line, polygon). Events are also assumed to have some domain supported type classification.

Given an assigned temporal setting for an observation expressed as either an interval or instant, Temporal Context is the set of events in some temporal relation (e.g. before, concurrent) with an observation's temporal setting and additionally having relevant spatial relations to the observation's SpatialSetting or expanded spatial context. Standard SPARQL does not support temporal queries, but using extensions to SPARQL we can retrieve events of a specified type that have occurred within some temporal range of the observation's temporal setting. We can also retrieve events that have occurred in a specific temporal interval relationship (before, meet, overlap, during, start, finish, equal) to a temporal setting interval or in the case of an instant, before or equal [30].

Events that qualify for Temporal Context by satisfying temporal relationships must also be evaluated for relations with the observation's SpatialSetting and Spatial Context sets. Events are first checked to see if they share a spatial setting with an observation and then checked for spatial relationships with an observation's extended Spatial Context.

4 Context Model Example

To illustrate the spatial dimension of our context modeling approach we use water quality observations collected for shellfish harvest monitoring. Shellfish (clams, mussels, and oysters) are filter feeders, so the quality of the waters in which they grow is a key factor in determining whether they are safe to eat. Marine water samples are collected and tested throughout the year to evaluate levels of pathogenic bacteria and the presence of high levels trigger shellfish bed closures. This monitoring setting has a number of context dependencies important for understanding the spatial and temporal dynamics of coastal pollution events and bacterial outbreaks. Complex system interactions exist between natural process events such as precipitation, temperature, and salinity changes and anthropogenic events such as wastewater treatment protocols, sewer or storrmwater discharges, or changes in land use-land cover. Temporal dependencies can arise as a result of stream chemistry reacting differently to rainfall events depending on season and weather [32,33,34]. Spatial dependencies include catchment setting, size of embayment, and number and size of freshwater inputs.

The shellfish harvest area water quality observation data [35] include a station location, date, sampling protocol (e.g. R = random), a fecal coliform count per 100ml seawater sample (Score), a laboratory test method (MFCOL= membrane filtration), some related observations on tide level and wind direction, and an adversity factor that includes for example: P= rain or mixed precipitation anytime within past 2 days (i.e. thunderstorms, rainfall more than a drizzle); T= thawing snow and ice melt; S= sewage treatment plant malfunction or bypass events; W= Waterfowl (10 or more), domestic or wild animals (i.e., at the station or in close enough proximity to have a possible impact). Table 3 shows an example water quality observation record [35]. Some level of contextual information is provided by the adversity factor but not in any formal way.

Table 3. Example of a shellfish growing area water quality observation record.[35].

Station	Date	Strategy	Score	Method	Collector	Adversity	Wind	Tide
WJ001.50	5/3/2012	R	80	MFCOL	EXT	P	NE	HE

For demonstration purposes, a subset of these observations was semantically annotated using parts of the OBOE ontology with the addition of a spatial setting specification. A Hydrologic Feature Gazetteer instantiated with features from the US National Hydrography Database (NHD) provides the basis for spatial context expansion. Features in the gazetteer are uniquely identified by their Geographic Names Information System (GNIS) number and associated with an official GNIS name.

A water quality monitoring station was specified as a subclass of a GeoSPARQL feature and each observation was assigned a unique identifier based on its station number (e.g. WJ001.50.345678). Because observations are taken at stations and stations are fixed, the spatial setting of an observation has a two part specification; an observation is assigned a station as a spatial setting, and a station is then assigned one or more spatial settings that may be specified as places, geometry, or both as shown below.

```
oboe: observationWJ003.021345 gem: hasSpatialSetting geo:
StationWJ003.02
geo:StationWJ003.02 gem: hasSpatialSetting
hgaz:gnis570752 #specifies a feature
geo:StationWJ003.02 geo:hasGeometry geo: PointWJ003.02
```

Spatial Context for an observation can be obtained by expansion of the spatialSetting to semantically related features (places) or to spatially related geometries. To create an expanded SpatialContext for a water quality observation taken at StationWJ003.02 with the feature based SpatialSetting, Staples Cove, we use the SPARQL query template shown in Table 2 on the Hydrologic Feature Gazetteer. The query retrieves a set of features hydrologically related to Staples Cove. Staples Cove is the mouth of three streams, Frost Gully Brook, Concord Gully Brook and Kelsey Brook. These streams and their relationship to the spatial setting form one possible spatial context for this observation. Spatial Context could be further expanded through inference on defined relationships. This prototype supports an example set of feature types and relationships and as such provides one example of how a semantically enhanced gazetteer could be used for flexible spatial context construction.

5 Summary

To be most effectively used, scientific observations can benefit from spatial and temporal context models. Building on the OBOE semantics for observations [3], this paper describes a model for open ended spatial and temporal context building for observations. Defining what constitutes spatial or temporal context is a context dependent problem and placing exact bound on these can be limiting. We address the spatial aspect of the problem by allowing features or places and relationships among features and places to define spatial context from narrow settings to expanded settings as a function of feature-feature relationships. An example water quality data set collected as part of a shellfish monitoring program was used for proof of concept. Future research needs to develop the temporal context model more fully and test the approach on larger data sets and different contexts. SPARQL queries for interacting with the context model are cumbersome for an average user and could benefit from further research on graphical interfaces and query rewriting to facilitate construction and interaction with context sets. Further investigation of effective visualization of observations within spatial and temporal context sets would also benefit researchers in exploring their observation data.

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