ISPRS Journal of Photogrammetry and Remote Sensing xxx (2013) xxx–xxx

Contents lists available at SciVerse ScienceDirect

ISPRS Journal of Photogrammetry and Remote Sensing

journal homepage: www.elsevier.com/locate/isprsjprs

Intelligent services for discovery of complex geospatial features from remote sensing imagery

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ARTICLE INFO

Article history:
Available online xxxx

Keywords:
Image mining
Geospatial services
Workflow
Semantic
Feature discovery
GIS
Complex geospatial features

ABSTRACT

Remote sensing imagery has been commonly used by intelligence analysts to discover geospatial features, including complex ones. The overwhelming volume of routine image acquisition requires automated methods or systems for feature discovery instead of manual image interpretation. The methods of extraction of elementary ground features such as buildings and roads from remote sensing imagery have been studied extensively. The discovery of complex geospatial features, however, is still rather understudied. A complex feature, such as a Weapon of Mass Destruction (WMD) proliferation facility, is spatially composed of elementary features (e.g., buildings for hosting fuel concentration machines, cooling towers, transportation roads, and fences). Such spatial semantics, together with thematic semantics of feature types, can be used to discover complex geospatial features. This paper proposes a workflow-based approach for discovery of complex geospatial features that uses geospatial semantics and services. The elementary features extracted from imagery are archived in distributed Web Feature Services (WFSs) and discoverable from a catalogue service. Using spatial semantics among elementary features and thematic semantics among feature types, workflow-based service chains can be constructed to locate semantically-related complex features in imagery. The workflows are reusable and can provide on-demand discovery of complex features in a distributed environment.

1. Introduction

The advancement of remote sensing technologies has increased significantly the capability of acquiring geospatial data. For example, the National Aeronautics and Space Administration (NASA)'s Earth Observing System (EOS) alone collects over 1000 terabytes of data annually (Clery and Voss, 2005). Remote sensing imagery has become an important source for the identification of geospatial features. The overwhelming volume of routine image acquisition has greatly outpaced the increase in the capacity of manual image interpretation by intelligence analysts. Automated methods or systems are needed to reduce the workload of human intelligence analysts and increase the possibility of prompt detection of interested geospatial features.

Methods of geospatial image mining and feature extraction have been commonly used to generate geospatial features from high-resolution imagery. The extraction of elementary ground features such as buildings and roads from remote sensing imagery has been studied extensively, and some effective methods have been made available (Gruen et al., 1995; Mena, 2003; Baltsavias, 2004; Michaelsen et al., 2010; Naouai et al., 2011). The discovery of complex geospatial features, however, is still an open issue. Detecting complex features from geospatial imagery is a promising approach for characterizing proliferation of Weapons of Mass Destruction (WMD), including nuclear. Complex geospatial features are spatially composed of elementary ground features (e.g., buildings for hosting fuel concentration machines, cooling towers, transportation roads, and fences). The spatial semantics (e.g. connectivity, adjacency, and intersection) can be used to identify geospatial features. Traditional image analysis approaches mainly exploit image features, such as color and texture, and to some extent, size and shape. These image features ignore important spatial relationships (Vatsavai et al., 2010a), without which complex (compound) features[1] that relate to facilities, such as factories or schools, cannot be accurately discovered.

In this work, spatial semantics are understood as spatial relationships among elementary features, and thematic semantics refer to

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[1] In the context of this paper, the terms "complex feature" and "compound feature", as well as "simple feature" and "elementary feature", are used interchangeably, although "complex feature" and "simple feature" are often used in the context of OGC standards (Percivall, 2003).

0924-2716/$ - see front matter © 2013 International Society for Photogrammetry and Remote Sensing, Inc. (ISPRS) Published by Elsevier B.V. All rights reserved.
http://dx.doi.org/10.1016/j.isprsjprs.2013.02.015

hierarchical relationships among feature types (e.g. the high school facility is a sub-category of the school facility). The former represent the spatial characteristics of complex features, and the latter represent the thematic characteristics of complex features. They can be combined together in feature discovery. The work in this paper addresses the discovery of complex geospatial features in a distributed geospatial service environment. It shows how workflows on feature discovery can be designed using semantics and then invoked using elementary features and spatial analysis services discovered from geospatial catalogue services. The novelty of the approach is that it effectively divides the task for identification of complex features in imagery into two independent steps, the simple feature extraction and complex feature discovery, and both spatial and thematic semantics are evaluated in feature discovery using a series of geoprocessing services computing spatial relations. This provides the flexibility of using different workflows for on-demand discovery of various types of complex features. In addition, the design of a feature catalogue service by combining the Open Geospatial Consortium (OGC)'s CSW-ebRIM (Catalogue Services for the Web – ebXML Registry Information Model) profile (Martell, 2008) and distributed Web Feature Services (WFSs) (Vretanos, 2010) provides a standard-compliant interface and information model for discovery of archived elementary features at the feature instance level, while previous work on feature catalogues focus more on the feature type based discovery.

The remainder of the article is organized as follows. Section 2 introduces examples to clarify the context in which semantics of complex features account in feature detection in remote sensing imagery and why service and workflow technologies are needed. Section 3 provides related work in literatures. Section 4 presents the approach and a walk-through of the feature detection process. Section 5 contains the discussion. Conclusions and future work are given in Section 6.

2. Motivation

2.1. Semantics of complex geospatial features

To illustrate the proposed solution, we use the following example as an illustration. Assume an intelligence analyst, John, wants to find schools near railways in the Providence District, Fairfax County, Virginia, US from remotely sensed imagery. The semantics of school facilities will play an important role in detecting schools in the imagery.

A school facility is spatially composed of elementary ground features such as buildings and grass fields. In the geospatial image mining and feature extraction, the algorithms for extracting ground elementary geospatial features such as buildings, field, roads, and railways have been studied for many years and are near mature (Gruen et al., 1995; Mena, 2003; Sohn and Dowmana, 2007; Mohammadzadeh and Zoej, 2010). This paper assumes that elementary geospatial features are already extracted from satellite imagery and other sources. In case only raw imagery is available or algorithms do not perform well, new algorithms or feature extraction services can be plugged in for on-demand extraction of elementary features.

Fig. 1 shows the example images for a high school (Fig. 1b), middle school (Fig. 1c), and an elementary school (Fig. 1d). High schools and middle schools typically include athletics tracks. A high school will also include a tennis court, while middle schools and elementary schools do not. An elementary school usually provides a playground, while high schools and middle schools do not. The semantics of school facilities can be represented using ontologies, which can make their semantics explicit and formal. A school ontology is provided for the case (Fig. 1a). The top-level entity is *FeatureType*, which is a generic concept. Its sub-concepts include high-level feature types from the Alexandria Digital Library (ADL) Feature Type Thesaurus, such as *HydrographicFeature* and *ManmadeFeature*. The *School* is a subtype of *Facility*, which is a kind of man-made features. *HighSchool* and *ElementarySchool* are subclasses of *School*. The conceptualization of *HighSchool* or *ElementarySchool* is based on the intentional meaning of concepts (Klien, 2007), and uses spatial relations to formalizing their spatial characteristics (Klien and Lutz, 2005). For example, buildings near a grass field and a tennis court could be a high school; buildings near a grass field and an athletics track could be either a high school or a middle school; buildings near a grass field and a playground maybe an elementary school. Such semantics can later be used in guiding service chaining for locating possible sites of complex features in imagery for intelligence analysts to further investigate. It is noted that the paper focuses on the use of semantics instead of formalization of semantics. A complete conceptualization of features, however, is out of the scope of this paper.

2.2. Why using service and workflow technologies?

Traditionally, geospatial image mining and feature extraction are performed in a siloed information environment. The interpretation of imagery by a few expert analysts fall far short of today's increasing demands for timely information extraction. As a result, many data may never been analyzed even once after collection. If semi-automated or automated technologies and approaches are available, they would significantly reduce the workload of intelligence analysts to find useful information from oceans of data. Web Services can significantly reduce the data volume and required computing resources at the end-user side, and are being used widely for problem-solving and scientific discovery in Spatial Data Infrastructure (SDI) (Kiehle et al., 2007; Zhao et al., 2012) or cyberinfrastructure (Hey and Trefethen, 2005; U.S. NSF, 2011). A Web Service is a software system designed to support interoperable machine-to-machine interaction over a network (Booth et al., 2004). With the standard interface, Web Services developed by different organizations can be combined as workflows to allow the widespread automation of data analysis and computation.

There is already extensive research on image processing algorithms in geospatial image mining and feature extraction. Users need technologies and flexible intelligent systems to discover complex geospatial features. Once users get the knowledge on the necessary feature components and their spatial relationships for a specific type of complex features, they would like to use the knowledge to locate features and compute spatial relationships among them in a distributed service environment. The need could be met by integrating workflow composition and execution, and chainable service technologies in a service-oriented environment.

3. Background and related work

This section describes some basic concepts (Sections 3.1 and 3.2) that help understand the approach. Next, it introduces related work, in particular the use of spatial relations, for identifying complex geographical concepts or features (Section 3.3). The related studies on geospatial service technologies that support service chaining and feature discovery are also introduced (Section 3.4).

3.1. Spatial relationships

Spatial relationships can be grouped into different categories: topological relations, distance relations, and direction relations (Egenhofer, 1989; Egenhofer and Franzosa, 1991; Shariff et al., 1998; Arpinar et al., 2006; Ellul and Haklay, 2006). The topological relations (e.g. *disjoint*) refer to properties such as adjacency,

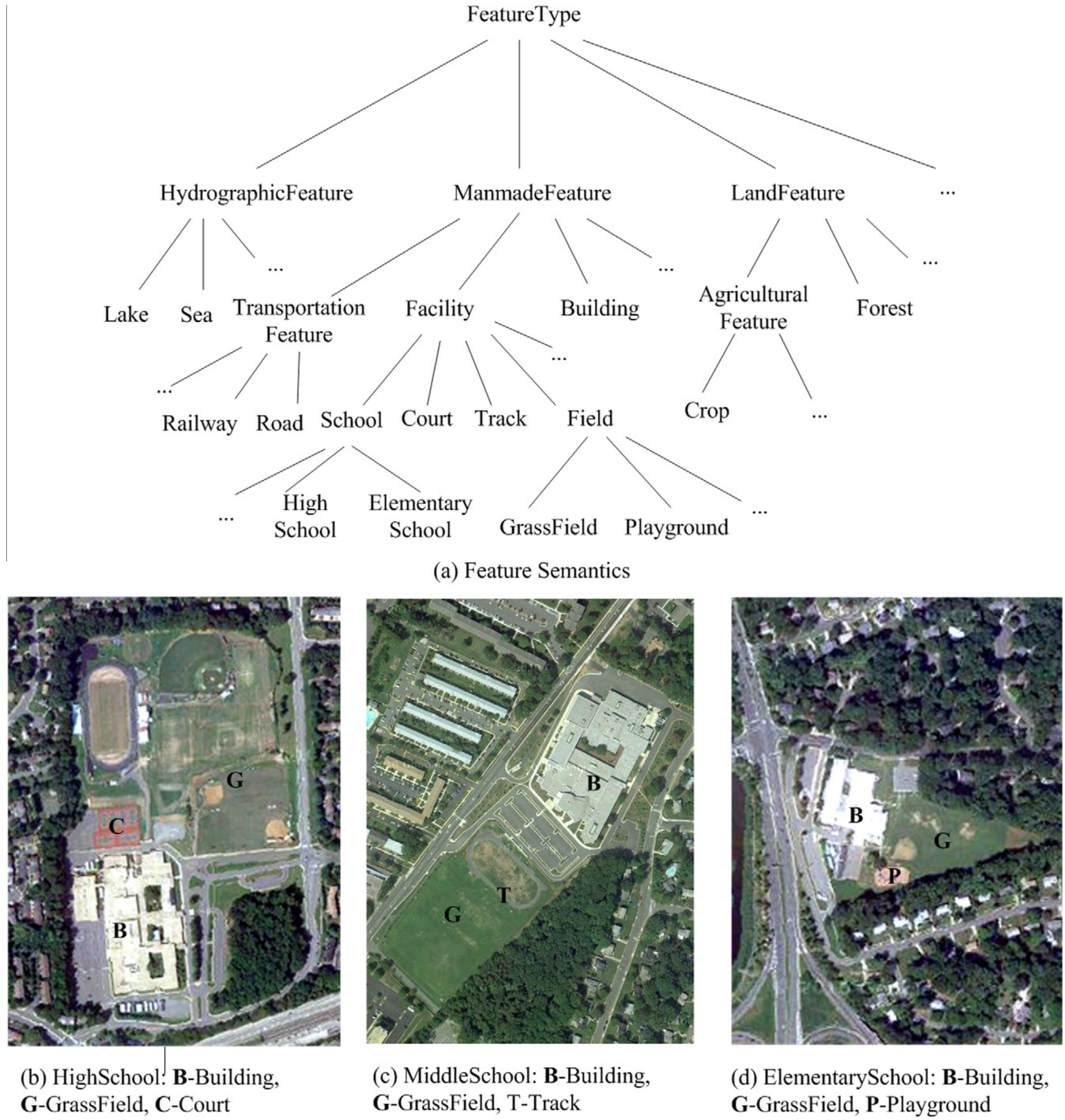

Fig. 1. Examples of complex features.

intersection, connectivity, and containment among spatial objects (Arpinar et al., 2006; Ellul and Haklay, 2006). They are invariant under topological transformation, such as rotation, translation, and scaling (Egenhofer, 1989). The distance relations (e.g. *close* and *far*) express the geographical distances among spatial objects, and reflect the concept of metric (Shariff et al., 1998). They change under scaling but stay invariant under translation and rotation. The direction relations (e.g. *east* and *north*), or called cardinal direction relations, denote relative directions among spatial objects (Arpinar et al., 2006). They are based on the existence of a vector space, and are subject to change under rotation while stay invariant under translation and scaling of the reference frame (Shariff et al., 1998).

Spatial relationships are often expressed using natural language terms (Shariff et al., 1998; Arpinar et al., 2006). These terms can be denoted as "fuzzy" relationships due to their inherent vagueness and precision associated with natural language expressions. For example, the *near* relation can be a *touches* relationship or *within* a 100-m distance. There is some work using fuzzy set for fuzzy representation of spatial relations (Bloch, 2005; Hudelot et al., 2008). The degrees to which relations hold are determined by fuzzy membership functions. Rather than attempt to represent the fuzziness of terms, one can still use a crisp approach, e.g., letting users unambiguously specify the meaning of a spatial relation (Robinson, 1990). Taking the *near* relation as an example, two objects can be defined to be near each other whenever their distance is less than a threshold (Denofsky, 1976). Once the threshold is specified by users, the *near* relation can be determined using a combination of primitive operators: *buffer* and *intersects*, which are well supported by today's spatial analysis algorithms. There are already two fundamental approaches on the definition of primitive topological relationships: the 9-intersection model (Egenhofer and Herring, 1990) and the Region Connection Calculus (RCC) model (Randell et al., 1992). Both of them can lead to the same set of topological relations. The OGC Simple Feature Access Common Architecture specification (Herring, 2011) adopts the 9-intersection model, and defines primitive relations including *Equals*, *Disjoint*, *Intersects*, *Touches*, *Crosses*, *Within*, *Contains*, and *Overlaps*. The work in this paper will rely on users to refine "fuzzy" relations into a set of primitive relations implemented by spatial analysis services, although solutions based on fuzzy set theory could be investigated in the future.

3.2. Geospatial Web Services

Web Service technologies are a set of technologies for the implementation of Service-Oriented Architecture (SOA) (Papazoglou, 2003). SOA provides an interoperable computing infrastructure for conducting advanced distributed geoprocessing tasks (Zhao et al., 2012). In the geospatial Web Services area, OGC is the major organization working on developing geospatial Web Services standards by adapting or extending the common Web Service standards. Through the OGC Web Services (OWSs) testbed, OGC has been developing a series of interface specifications under the OGC Abstract Service Architecture (Percivall, 2002). OWS follows the publish-find-bind paradigm in the SOA and defines discovery, description, and binding layers corresponding to UDDI (Universal Discovery Description and Integration) (OASIS, 2004), WSDL (Web Services Description Language) (W3C, 2007a), and SOAP (Simple Object Access Protocol) (W3C, 2007b) in the W3C (World Wide Web Consortium) architecture. Service composition introduces a new layer into SOA, chaining, which combines services into a dependent series to accomplish a complex task.

In the discovery layer, OGC CSW specifies a standard interface for a geospatial catalogue service that can be used to advertise and discover shared geospatial data and services. OGC has developed and recommended the CSW-ebRIM profile, which adopts ebRIM, a standard defined by the Organization for the Advancement of Structured Information Standards (OASIS), as the information model for specifying how catalogue content is structured and interrelated (Martell, 2008). The ebRIM specifies the metadata for information resources by using a set of classes and relationships among these classes. It is a general information model and has been extended by CSW-ebRIM to record domain-specific metadata. Using the CSW-ebRIM profile, it is possible to develop a metadata catalogue for geospatial resources including elementary features provided by distributed WFSs. Section 4.2 will discuss how to make extensions to the CSW-ebRIM for discovering elementary features.

3.3. Identification of complex features

Feature extraction from remote sensing imagery provides a time-efficient and cost-effective way to generate geospatial data in a vector format. Mansourian et al. (2008) present the design and implementation of a feature extraction Web Service. An automatic feature extraction algorithm is provided in the Web Service to allow online extraction of roads from satellite imagery. There are already substantial studies on extraction of elementary features, such as buildings and roads, from imagery (Gruen et al., 1995; Baltsavias, 2004; Mena, 2003; Naouai et al., 2011; Michaelsen et al., 2010). The research on automatic discovery of complex geospatial features is still rather rare and requires the consideration of semantics or spatial pattern of complex features.

In traditional aerial photo interpretation, the spatial/thematic semantics could be related to fundamental elements such as site and association (Jensen, 1996). There are some approaches on extraction of semantic information and semantic labeling of features in high-resolution imagery (Tobin et al., 2006; Gleason et al., 2010; Vatsavai et al., 2010a and Vatsavai et al., 2010b). Typically, such algorithms use training data in the form of image segments with known objects and then use various statistics to match the training data with the imagery. Compared to such one-step approaches, the approach described in this paper can be considered as a two-step approach, with step 1 being to identify the location and type of elementary ground features (such as buildings and roads) from high-resolution imagery, which has relatively mature technologies, and step 2 being to extract high-level semantic information (such as nuclear fuel concentration sites and school facilities) by discovering compound ground features from spatial relationships among the elementary features.

In the cartography and geographical information system (GIS), a geospatial feature is an abstraction of real world phenomena (ISO, 2002) and has its geometric data types such as points, lines, and areas. While these types are well suited to represent simple, elementary features, the flexible combination of these geometric types for representing complex features is not easy to be supported in current GIS. As a result, the representation of a complex feature often chooses to fit a simple shape through cartographic generalization (Varanka, 2011), such as representing a school as a dot on a map. On the other hand, the semantic meaning of feature assemblages in formulating a complex feature has its value in improving data discovery and interoperability. Therefore, Varanka (2011) suggests the use of ontology to capture such semantics.

The identification of complex features shares similarity with the work on semantic annotation of geospatial data using complex geospatial concepts. The role of spatial relations in defining and identifying complex geospatial concepts is investigated in the Spatial Data Infrastructure (SDI) (Klien and Lutz, 2005). By computing spatial relations among spatial entities, the spatial entity that conforms to a characteristic set of relations with other entities can be referenced to a corresponding geospatial concept. For example, a land unit can be identified as a floodplain if it fulfills the three criteria: adjacent to a river, flat, and at most 2 m higher than the adjacent river. For each criterion, spatial characteristics are extracted and analyzed. The final set of land units is created by intersecting three result sets from analysis steps for satisfying the criteria. The results are finally presented to users for verification. The semantic annotation of "floodplain" can then be created automatically. Klien (2007) further suggests the use of rules for partly automating the semantic annotation process after spatial predicates (i.e., spatial properties and relations), such as adjacent, are computed using the previous approach in Klien and Lutz (2005).

Lüscher et al. (2009) propose the use of Bayesian inference for deriving complex geographic concepts. For example, a terraced house is defined by its relations to other concepts such as yard, building, and house. Such semantics are named as spatial patterns, formalized through ontologies, and used to drive the pattern recognition process. Once facts about spatial predicates are generated from spatial analysis operations in GIS and exported to the knowledge base, the pattern classification process, such as Bayesian inference, instead of the rule-based approach in Klien (2007), can be carried out to infer instances of ontological concepts.

Nevertheless, aforementioned methods associate spatial predicates with spatial analysis methods in an ad hoc manner without formalizing the whole analysis process, e.g., how different spatial predicates can be computed orderly in the derivation process, which, however, is an open issue and may need a workflow

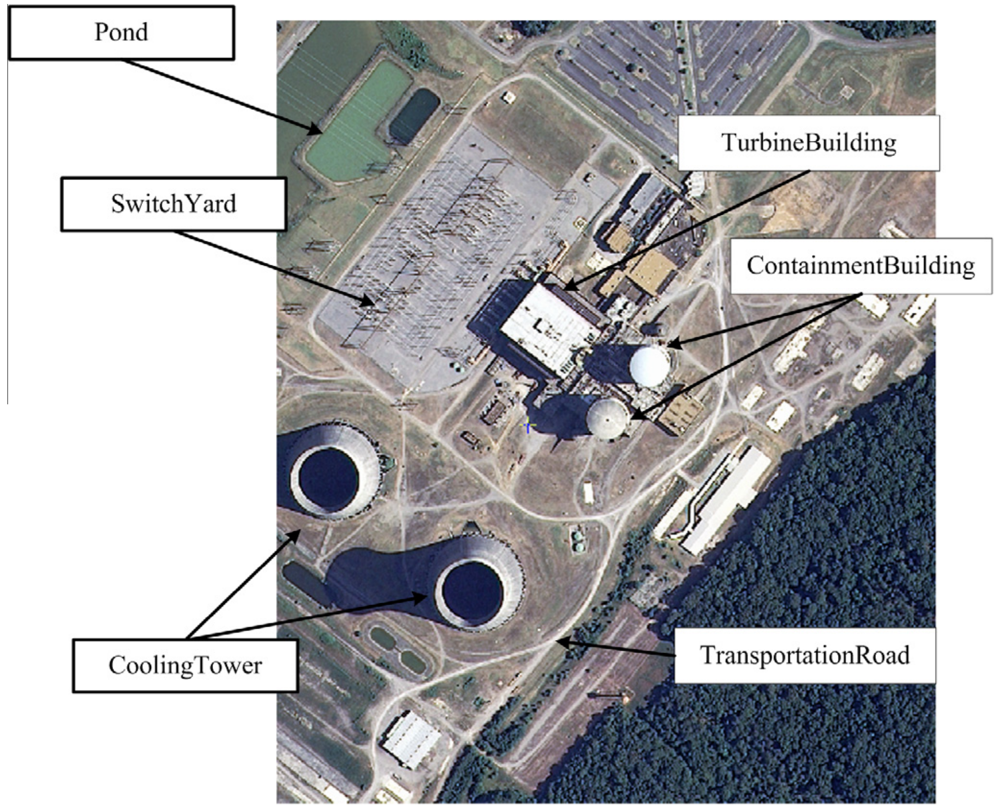

Fig. 2. An example of a nuclear power plant.

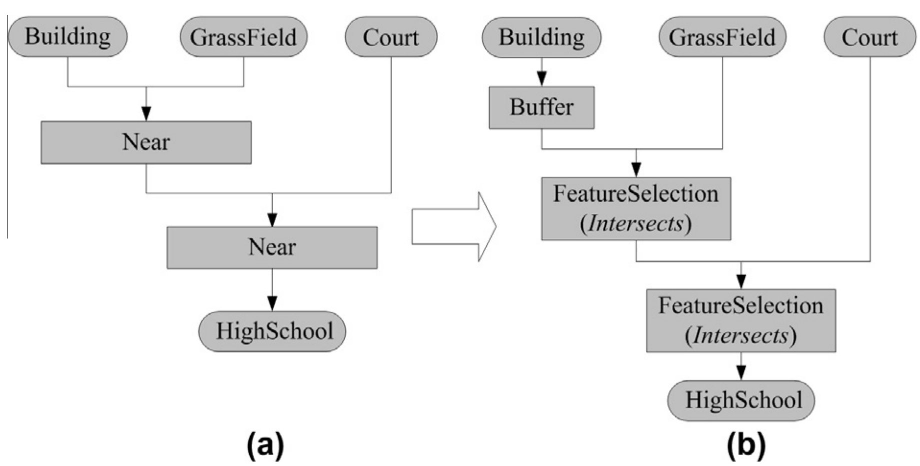

Fig. 3. Using semantics to create workflows.

approach (Klien and Lutz, 2005). In addition, the implementation of spatial analysis methods in existing methods does not consider the distributed geoprocessing environment such as SDI or Cyberinfrastructure, which are open and highly dynamic. These issues are addressed by the workflow composition and execution under a Service-Oriented Architecture (SOA) in this paper.

3.4. Service chaining and data discovery

In the context of SOA, spatial analysis functions are provided as loosely-coupled Web Services, and chained together as workflows to execute complex geoprocessing tasks (Brauner et al., 2009). OGC Web Services, W3C SOAP-based Web Services, and RESTful services are available for implementation of services. Some efforts have been devoted to make them work together, such as defining WSDL for OGC services (Sonnet, 2005), and using WSDL 2.0 as the bridge between REST and W3C Web Service (W3C, 2007a,b; Lucchi et al., 2008). Jager et al. (2005) presented a workflow framework for composing and executing Web Services in the Kepler system. Some efforts propose the use of the Web Services Business Process Execution Language (WSBPEL, BPEL for short) (OASIS, 2007) to support geospatial service chains (Fleuren and Muller, 2008; Friis-Christensen et al., 2009; Yu et al., 2012; Zhao et al., 2012). In addition to the BPEL-based service chaining approach, the OGC Web Processing Service can also be used for service chaining (Stollberg and Zipf, 2007). However, a comparative analysis shows that the BPEL-based implementation is more mature (Friis-Christensen et al., 2009). There are also some semantics based approaches on automating

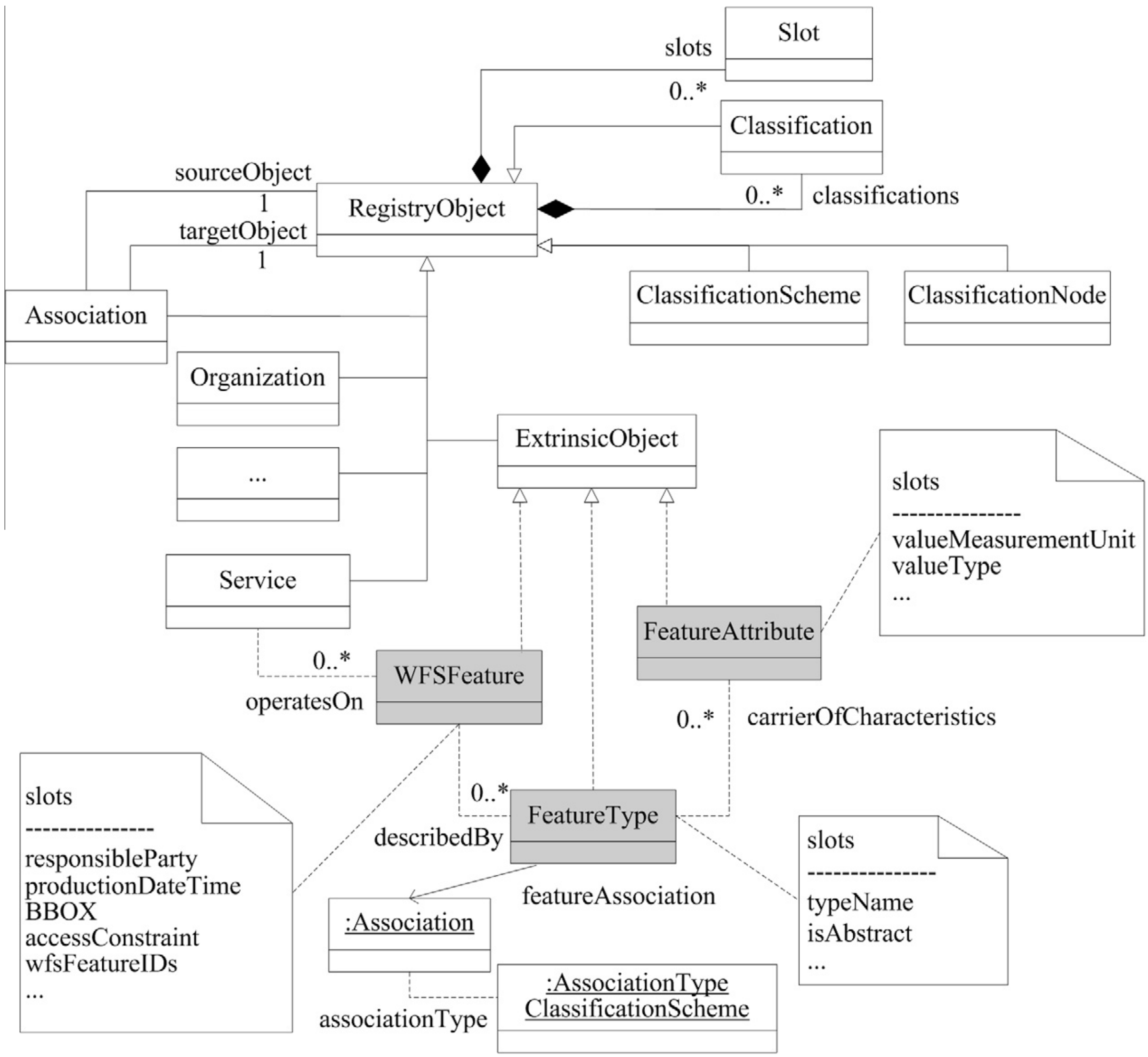

Fig. 4. The extended ebRIM model to support feature types and instances.

the chaining of geospatial services (Yue et al., 2007; Fitzner et al., 2011). The work in this paper uses ontologies to help intelligence analysts design service chains. The BPEL-based service chaining is used for feature discovery.

In the distributed service environment, the features extracted from imagery or other ancillary data are registered in catalogue services such as the OGC CSW to facilitate the discovery. Geographic features have two levels: instances and types (ISO, 2005a). Feature types are defined as classes of features (feature instances) that have common properties. Existing approaches for feature discovery in catalogue services focus on the feature discovery at the feature type level instead of the feature instance level (Lutz and Klien, 2006; Stock et al., 2010). This is due to the unprecedented number of feature instances, which could be impractical to manage metadata for each of them. Differing from the catalogue approach, Zhang et al. (2010) provide a semantics-based approach for searching feature instances using distributed Web Feature Services. All WFS features are indexed in a file for an efficient search. The index file is maintained by a service broker. The work in this paper supports the search of feature instances by combining the interoperable CSW-ebRIM profile and WFS services. In the back end, a two-step approach is proposed, which uses feature types to locate WFSs in the first step, and then search feature instances in distributed WFSs in the second step. In the front end, the feature instances are returned to CSW requesters following the catalogue information model. The CSW-ebRIM is extended to support queries on feature instances, which can be seen as an extension to the feature type based discovery proposed by Stock et al. (2010).

4. Approach for discovery of complex features

The discovery of complex features in the context of this paper includes both the orchestration of workflow based service chains and discovery of elementary features as inputs to service chains. Section 4.1 introduces the strategy on how to use spatial and thematic semantics in assisting the construction of workflow models. The models are converted into executable service chains by binding individual services and elementary features discovered from CSW (Section 4.2). The approach is illustrated in the school example step by step in Section 4.3.

4.1. Using semantics of complex features to create workflows

The spatial semantics/pattern of complex features includes elementary features and spatial relationships among them. The

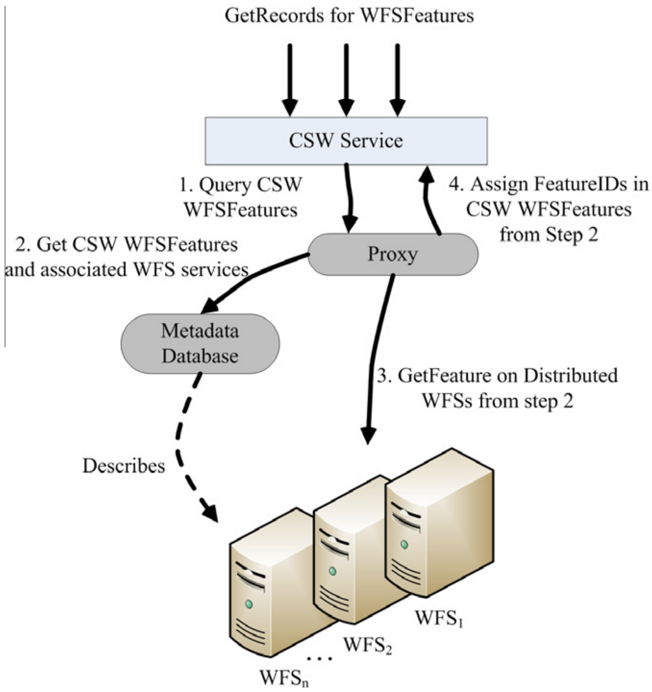

Fig. 5. Architecture and workflow in supporting the query of elementary features.

elementary features could be member features and surrounding features. The member features are features that are constituents of complex features such as cooling towers as a component of nuclear power plants. The surrounding features are the features that can characterize the surrounding environment of complex features. For example, nuclear power plants are far away from populated areas, while school facilities are located in the populated areas. Fig. 2 shows a nuclear power plant as a complex feature. It consists of a group of ground features (e.g., containment buildings, ponds, switch yard, and transportation roads).

The spatial pattern of complex features can be represented using conjunctions of a set of spatial relations, which may be "fuzzy" relations and requires humans' interpretations, such as reactors are surrounded by a fence and near the cooling tower and switch yard in the nuclear power plant, and buildings are near the sport field and court in the high school. These spatial relations (e.g. *near*) are refined to a set of primitive relations. The primitive relations such as those stated in the OGC simple feature specification are well defined, mutually exclusive, and can be interpreted by computer programs. Each primitive is implemented by a GIS operator in traditional component-based GISs or an atomic service in service-oriented GISs. The evaluation of the spatial pattern in detecting complex features is similar to traditional spatial query processing approaches in that non-primitive relations in spatial queries are transformed into evaluation plans consisting of a set of primitive relations (Clementini et al., 1994). However, the evaluation in a service-oriented information environment requires the dynamic discovery of geoprocessing services as well as feature inputs to service chains in supporting the analysis of spatial relations.

The spatial analysis operators in supporting the computation of primitives of spatial relations can be implemented using the feature selection service. A feature selection service supports topological relationships defined by the OGC simple feature specification between any two classes of features in point, line, and polygon types. The conjunctions of a set of spatial relations in characterizing the spatial pattern of a complex feature can be formalized through workflow descriptions. Using spatial semantics of complex features such as buildings near the sport field and court, workflows like Fig. 3a can be created. The "fuzzy" relations are further refined using unambiguous primitive operators, and then workflows like Fig. 3b are generated. The domain logic of the workflow is that the sites of complex features can be located by one type of its elementary features following the specific spatial relationships with other types of elementary features. The use of workflows for formalizing the analysis process of complex features takes advantages of the well-defined formalism such as data flows and control flows in existing workflow languages, and allows the adjustment of implementation such as the buffer width when specifying the *near* relation according to the context.

While spatial semantics can assist the creation of workflows for one single goal (i.e., a specific type of complex feature), the thematic semantics of complex features can help generate workflows by formulating multiple subgoals (i.e. multiple complex features that follows the subsumption relationships to the target feature). For example, different subtypes of school facilities have their own spatial patterns. Thus, different workflows can be generated according to their specific patterns, and combined together in discovering school facilities.

4.2. Discovery of elementary features to invoke workflows

In a distributed environment like the Web, the features may be extracted from imagery by different algorithm vendors and provided by independent data providers. Services in a workflow for determining the spatial pattern of features may also be scattered among multiple spatial analysis service providers. The workflow needs to be converted into an executable service chain when all required analysis services and inputs, often discovered through a geospatial catalogue service, are available. By extending the information model in the CSW-ebRIM profile, geospatial data and services can be registered and discovered from interoperable catalogue services. Previous work has demonstrated the registration and discovery of coverage data and geoprocessing services in the CSW-ebRIM profile (Yue et al., 2011). The work in this paper extends previous work by combining the CSW-ebRIM with distributed WFSs to discover elementary features. The key issues are the extension of the information model to support the search of feature data, and query processing by integrating CSW-ebRIM and distributed WFSs.

The ebRIM information model defines a set of classes for organizing metadata. Fig. 4 shows relationships of metadata classes defined by ebRIM. The core class is the RegistryObject. Other classes in the information model are derived from this class. A RegistryObject can have multiple instances of Slot to record its attributes. Relations between RegistryObjects are represented using instances of Association. Each association has an associationType attribute that identifies the type of that association. The ExtrinsicObject class is an extension point. Domain-specific metadata classes can be derived from it. The ebRIM also provides a ClassificationScheme class, which defines a tree structure made up of classification nodes that can be used to describe a taxonomy. A Classification instance classifies a RegistryObject using a ClassificationNode from a ClassificationScheme.

The registration of feature data takes advantages of extension points offered by ebRIM. These extension points include new types of classes, new kinds of associations and classifications, and additional slots. The General Feature Model (GFM) from ISO 19109 defines the concepts (types, attributes, associations, and behaviour) used to specify features and how these concepts are related (ISO 19109, 2002). These concepts can be formalized as feature type, feature association, feature attribute, and feature operation in a Feature Type Catalogue defined by the ISO 19110 (ISO, 2005a). The dashed lines in Fig. 4 show extensions to support these feature concepts using extensibility points of ebRIM. They include: (1) creating three new classes in ebRIM for recording features, feature

Table 1
An example of WFSFeature in XML.

```
<?xml version = “1.0” encoding = “UTF-8”?>
<wrs:ExtrinsicObject xmlns:wrs = “http://www.opengis.net/cat/wrs” xmlns:rim = “urn:oasis:names:tc:ebxml-regrep:xsd:rim:3.0” xmlns:gml = “http://
   www.opengis.net/gml” xmlns:xml = “http://www.w3.org/XML/1998/namespace” id = “urn:uuid:146785E6-4618-44cb-BF2A-F513B5AEDA45”
   objectType = “urn:ogc:def:ebRIM-ObjectType:OGC:WFSFeature” status = “Submitted” mimeType = “application/octet-stream” isOpaque = “false”>
  <rim:Name>
    <rim:LocalizedString xml:lang = “en-US” charset = “UTF-8” value = “buildings”/>
  </rim:Name>
  <rim:Description>
    <rim:LocalizedString xml:lang = “en-US” charset = “UTF-8” value = “buildings extracted from images and provided by WFS”/>
  </rim:Description>
  <rim:Slot name = “http://purl.org/dc/terms/spatial” slotType = “urn:ogc:def:dataType:ISO-19107:2003:GM_Envelope”>
    <wrs:ValueList>
      <wrs:AnyValue>
        <gml:Envelope srsName = “urn:ogc:def:crs:EPSG:4326”>
          <gml:lowerCorner>−77.536718 38.605617</gml:lowerCorner>
          <gml:upperCorner>−77.041362 39.057678</gml:upperCorner>
        </gml:Envelope>
      </wrs:AnyValue>
    </wrs:ValueList>
  </rim:Slot>
  <rim:Slot name = “responsibleParty” slotType = “urn:oasis:names:tc:ebxml-regrep:DataType:ObjectRef”>
    <rim:ValueList>
      <rim:Value>urn:uuid:F822DC7D-0C1B-45C6-9C40-FED5E268BF94</rim:Value>
    </rim:ValueList>
  </rim:Slot>
  <rim:Slot name = “accessConstraint” slotType = “urn:oasis:names:tc:ebxml-regrep:DataType:String”>
    <rim:ValueList>
      <rim:Value>NOT_ACCESS_RESTRICTED</rim:Value>
    </rim:ValueList>
  </rim:Slot>
  <rim:Slot name = “orderable” slotType = “urn:oasis:names:tc:ebxml-regrep:DataType:String”>
    <rim:ValueList>
      <rim:Value>false</rim:Value>
    </rim:ValueList>
  </rim:Slot>
  <rim:Slot name = “nativeCRSs” slotType = “urn:oasis:names:tc:ebxml-regrep:DataType:URI”>
    <rim:ValueList>
      <rim:Value>urn:ogc:def:crs:EPSG:32618</rim:Value>
    </rim:ValueList>
  </rim:Slot>
  <rim:Slot name = “nativeFormat” slotType = “urn:oasis:names:tc:ebxml-regrep:DataType:String”>
    <rim:ValueList>
      <rim:Value>ESRI_Shapefile</rim:Value>
    </rim:ValueList>
  </rim:Slot>
  <rim:Slot name = “supportedFormats” slotType = “urn:oasis:names:tc:ebxml-regrep:DataType:String”>
    <rim:ValueList>
      <rim:Value>GML</rim:Value>
      <rim:Value>ESRI_Shapefile</rim:Value>
    </rim:ValueList>
  </rim:Slot>
  <!—List of internal feature IDs in the associated WFS –>
  <rim:Slot name = “wfsFeatureIDs” slotType = “urn:oasis:names:tc:ebxml-regrep:DataType:String”>
    <rim:ValueList>
      <rim:Value>3</rim:Value>
      <rim:Value>5</rim:Value>
      <rim:Value>...</rim:Value>
    </rim:ValueList>
  </rim:Slot>
  ...
</wrs:ExtrinsicObject>
```

types and attributes, i.e., WFSFeature, FeatureType, and FeatureAttribute. WFSFeature is a metadata class for a feature dataset. It can be described by a FeatureType that records common characteristics of the dataset, and each of the common characteristics is recorded using a FeatureAttribute. (2) reusing the ebRIM Service class for supporting feature operations; (3) adding slots to declare properties of classes; and (4) building new associations based on relations among classes such as associations between feature types and feature attributes, and associations between extracted features and source imagery. The approach is similar to the ebRIM-based feature type catalogue proposed by Stock et al. (2010). The differences are that feature instances are supported in the information model and we reuse the Service class instead of a new class on feature operation to support the behaviour semantics of features.

The extended catalogue contents are queried through the standard CSW interface. The legacy implementation of CSW needs to be extended to incorporate WFS services to support the query processing and response formulation. Fig. 5 depicts the architecture and workflow to support the feature search such as “find a railroad near George Mason University”. The query on the WFSFeature can

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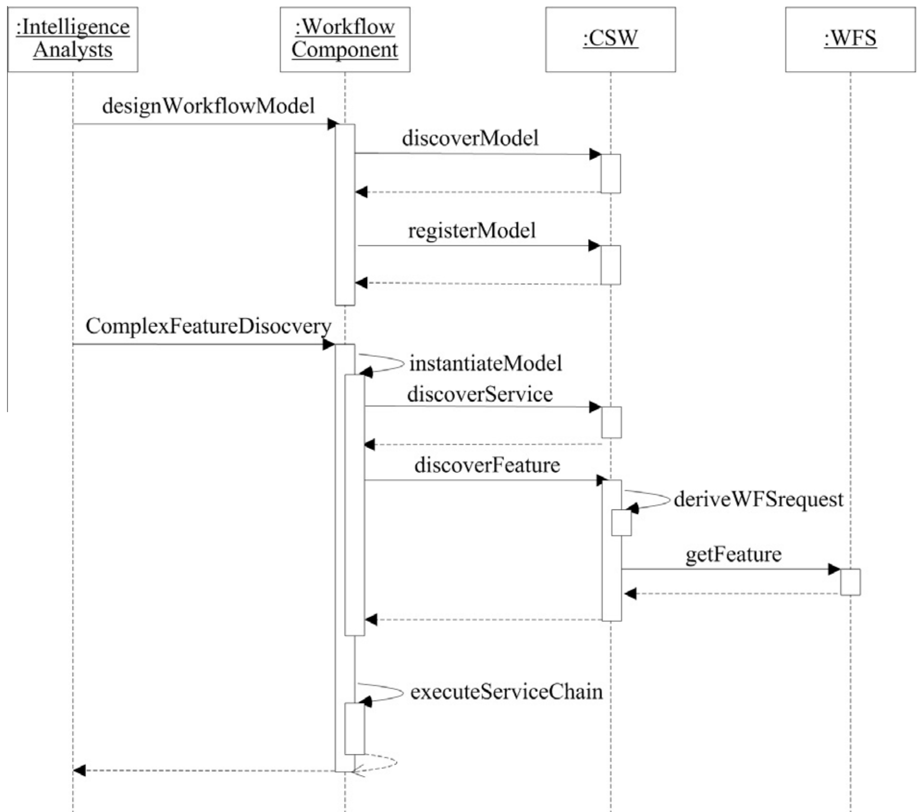

Fig. 6. A general sequence diagram supporting the case study.

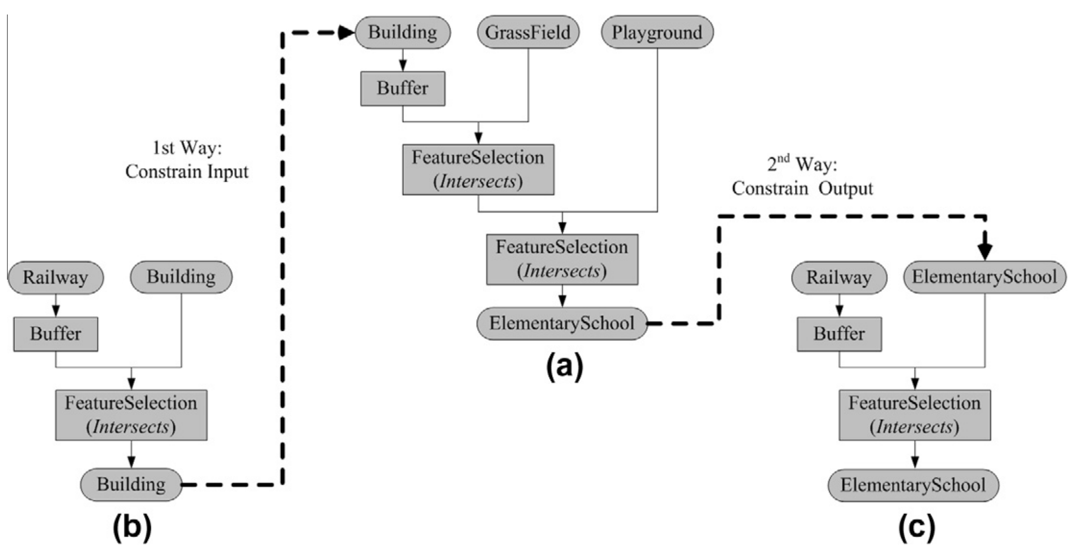

Fig. 7. Workflow modeling for answering the question.

be formulated using OGC filters and submitted using the standard GetRecords operation. On the backend of the CSW service, a proxy component specifically for handling the feature search is added. It searches the metadata database for WFSFeature instances that have the specified feature type (using the describeBy association) and spatial/temporal constraints. The instances currently do not include internal feature IDs. Instead, the internal feature IDs are dynamically retrieved based on the queries dispatched to WFS services associated (through the operationsOn association) with the WFSFeatures. Those IDs returned by WFS queries are assigned to related WFSFeature instances in the response to the GetRecords operation. Table 1 shows an example of a WFSFeature instance responding to a feature search. It includes metadata for a feature dataset and a list of feature IDs. The "objectType" property defines that the object is an instance of WFSFeature. Metadata such as spatial bounding box, spatial reference, and data format are recorded using slots. Feature IDs are listed using the slot "wfsFeatureIDs".

4.3. Walk through for examples

The school example in Section 2 is used primarily to illustrate the applicability of the approach. The walk-through feature detec-

Fig. 8. BPEL diagram for the feature discovery chain.

tion process follows a general process in Fig. 6. It has been supported in tools developed by the GeoBrain online system including the abstract model designer and GeoBrain Online Analysis System (GeOnAS) (Di, 2004; GeoBrain, 2011; Han et al., 2011). GeoBrain is a standard-based geospatial Web Service system aiming at mobilizing NASA data and information through Web Service and workflow management technologies. It allows users to dynamically and collaboratively develop Web-executable geospatial process models and service chains. Geoprocessing workflows are supported by process modeling and process model instantiation (Yue et al., 2009). The process modeling generates a workflow process model consisting of the control flow and data flow among process nodes. Each process nodes represents one type of individual services that share the same functional behaviours such as functionality, input, and output. The intelligence analysts design workflow models using semantics for complex features from existing ontologies (*designWorkflowModel*). Existing models can be discovered from the CSW and reused in the designing process (*discoverModel*), and new workflow models can also be registered in the CSW (*registerModel*) (Fig. 6). During the model instantiation process, the workflow process model is instantiated into a concrete workflow or executable service chain (*instantiateModel*) by dynamically binding individual spatial analysis services (*discoverService*) and feature data discovered from the catalogue service (*discoverFeature*). The specific steps on discovering school facilities are shown as follows:

(1) Creating ontologies for school facilities that include both spatial and thematic semantics. Although there are different types of school facilities, this case use the high school and elementary school for the demonstration. The high school has the following parts: building, grass field, and tennis court, while the elementary school has building, grass field, and playground. The parts in a complex feature follow the spatial relation *near*.
(2) Building workflow models for school facilities. The intelligence analyst, John, designs workflows by following the idea in Section 4.1. The “fuzzy” relation *near* is refined to the

Fig. 9. Decision support result.

precise and unambiguous primitive relations defined in the OGC simple feature specification. The workflow model for the high school is already shown in Fig. 3b, and the workflow model for the elementary school is shown in Fig. 7a.

(3) Extending workflow models according to the application requirement. John would like to find schools near railways. In this case, both complex features and elementary features are involved in the question. The *near* relation in the question, again, can be refined using the buffer and feature selection services. There are two ways to extend the workflow model for school facilities to enable its spatial relation with railways in the question. The first way is to impose the spatial constraint on the input elementary features of the workflow model for schools (Fig. 7b and a), and the second way is to impose the spatial constraint on the output (Fig. 7a and c). Both can answer the question, yet can show different performance in execution.

(4) Binding inputs and services for workflow models. The area of interests is located in the Providence District, Fairfax County, Virginia, US, which acts as the spatial filter to find elementary features such as railways and buildings in CSW. Web Services are also discovered using the CSW. In this case, the feature buffer and selection services provided by GeoBrain are discovered.

(5) Generating the BPEL description for the service chain. Once the input features and services are available for the workflow model, a concrete workflow is generated and can be represented using the BPEL syntax. Fig. 8 shows a BPEL diagram for detecting either elementary schools (when its inputs include buildings, grass fields, and playgrounds) or high schools (when its inputs include buildings, grass fields, and courts). The first two services find features near railroads, and the last three services determine the sites of potential schools based on spatial relations among those features. The right part of Fig. 8 shows an example set of features that can demonstrate the service chain. The BPEL description can be deployed into a BPEL engine and running as a new Web Service.

(6) Decision support analysis. The BPEL service is invoked and results are loaded in a user interface. John determines values of buffer distances in Fig. 7 according to the application context. For example, the buffer distance for the railway can be 1 km, while the buffer distance for the buildings could be 100 m. Source imagery can be retrieved based on the ebRIM associations between elementary features and source imagery. Fig. 9 shows the resulting features overlaid on the source image. Based on spatial relations among different types of features, a location of an elementary school could be identified, shown by the annotation in the figure.

The approach can work with different complex features. Taking a nuclear power plant as an example, it generally includes the following parts: containment building, cooling tower, ponds, and switch yard. They also follow the *near* relation. The first step would be to detect these elementary features using existing image processing algorithms. For example, a containment building is cylindrical and has a dome-shaped roof. It can be detected using remote sensing data such as the combination of LiDAR data and multispectral imagery (Awrangjeb et al., 2010). Once these elementary features are available, the rest of steps will be similar to the school case: computing spatial relations among elementary features using workflow modeling and service chain execution. Fig. 10 shows a workflow and features used to locate the site of a nuclear power plant. Buildings are stored in a WFS service. WFS defines the GetFeature operation that can be used to select containment buildings in an area of interest (Fig. 10a). The spatial relations between buildings and other features (cooling tower, pond, and switch yard) (Fig. 10b–d) can be analyzed step by step. Finally, features that satisfy the relations are overlaid with source imagery (Fig. 10e). It is also possible to add more restricted relations such as buildings surrounded by a fence. This may require a combination of the LINE-To-POLYGON conversion (e.g., fences as lines need to be converted to polygons) and *within* spatial operators. Such a requirement can still be satisfied by the workflow approach since it provides transparency for consuming semantics and offers flexibility for adjusting service chains.

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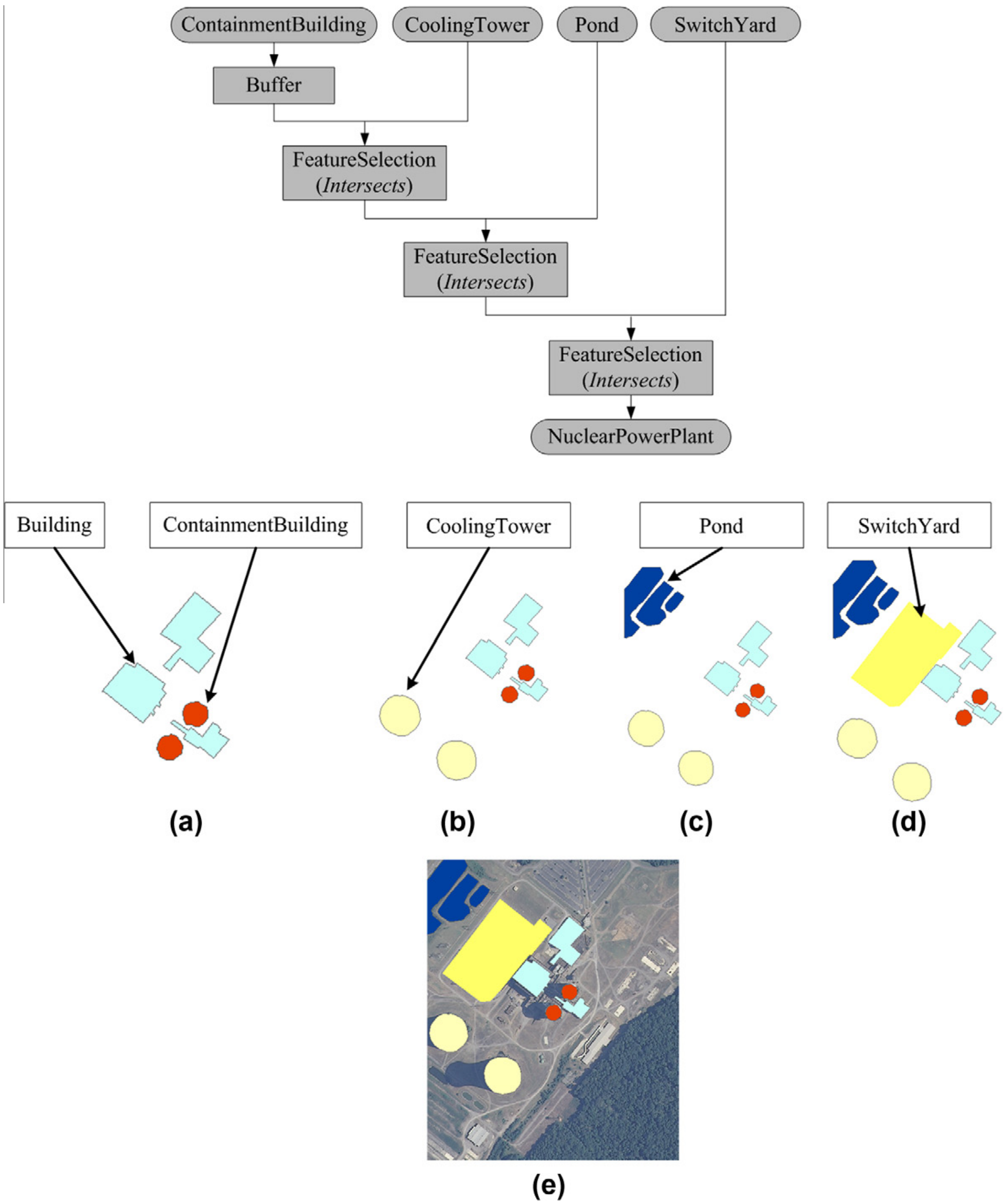

Fig. 10. Workflow for the nuclear power case.

5. Discussion

The proposed approach uses Web Services for computing a characteristic set of spatial relations among elementary features. The complex feature discovery process thus is performed in a distributed information environment. The environment is open and dynamic, where imagery, extracted features, and auxiliary data such as LiDAR data or archived features in different types could be discovered and bound dynamically. The service technologies and interoperable geospatial standards allow these data to be easily accessible. The service computing using distributed spatial analysis services provides powerful computing facilities and algorithm repositories for on-demand feature discovery. Traditional feature discovery in imagery, however, works in a siloed environment, where data sources or computing resources are often limited.

The chainable service technologies provide possibility for workflow composition and execution. The essence of the workflow approach on discovering complex features is to locate one of its member features that follows specific spatial relationships with other features. The resulting features can be used to locate the possible sites of complex features in massive volumes of remotely sensed imagery. The approach has the benefits of automation and intelligence. The discovery process can be automated as a workflow-based service chain, which as a whole can be conceived of as a service and executed dynamically once input elementary features are available. The execution returns only a limited number of imagery containing the potential sites to intelligence analysts for further investigation, thus lowering the burden of intelligence analysts, who traditionally have to manually interpret each image to capture potential complex features. This is particular useful in the national security domain such as automatic detection of suspicious WMD proliferation facilities using remotely sensed imagery.

The semantics of complex features are the key to generate workflows. In this paper, spatial semantics are associated with thematic semantics for feature detection. One assumption here is that elementary features and spatial relationships among them should characterize the specific type of complex features and differentiate it from other types of complex features. However, it is not trivial to select such a characteristic set since some facilities may share similar spatial characteristics. For example, in the school case, although in U.S. kindergartens are part of elementary schools, other countries may treat them as two different types of facilities. If kindergartens share the same characteristics with elementary schools, the approach will return both of them. On the other hand, a relaxed set of characteristics (e.g., a set of spatial relations that could characterize more than one type of facilities) could still return a reduced number of imagery by applying on-demand execution of workflows. This is useful for fast detection of possible facilities in massive volumes of remotely sensed imagery.

Semantic heterogeneity is an important issue in a distributed service environment (Lutz et al., 2009). For example, there might be different feature type schemas for elementary features such as buildings. A shared common ontology could be used to overcome such semantic heterogeneity when discovering features (Lutz and Klien, 2006). If different ontologies are used in annotating feature types, ontology matching, i.e. matching semantically related concepts, can solve the semantic heterogeneity at a higher level (Euzenat and Shvaiko, 2007; Vaccari et al., 2012). A semantic catalogue service, based on integration of a shared ontology and a geospatial catalogue service, has been explored (Yue et al., 2011). The ebRIM can be extended using ISO 19115 Geographic Information – Metadata (ISO, 2003) and ISO 19119 Geographic Information – Services (ISO, 2005b). For example, some new attributes can be added to the WFSFeature class based on ISO 19115. The semantic catalogue service can be further applied in discovering feature instances. Ontologies for feature types can be used for semantics-based feature discovery at the type level. At the instance level, where feature instances with semantically-correct feature types are provided by distributed WFSs, catalogue information model can support queries to return feature instances. As a future work, we will investigate this in detail.

While the approach in this paper uses workflows to formalize analysis steps for discovering complex features, the geospatial Semantic Web community tends to use the ontology based inference and matching for deriving complex concepts (Klien, 2007; Lüscher et al., 2009; Varanka and Jerris, 2010). Spatial predicates are generated using GIS operators, and encoded using Web Ontology Language (OWL). An OWL can be viewed as an RDF graph composed of triples (Subject, Predicate, and Object) (W3C, 2009). A RDF triple store, as a knowledge base, can be combined with rules or pattern classification to infer instances of complex concepts. If semantic Web Service technologies are used, it is also possible to store service semantics in RDF stores, and query and compose them based on ontologies for complex features. The detection task is decomposed into a series of semantic services computing spatial relations among elementary features. Such a process could be automated once an ontology for a type of complex features is available. The final workflow models, encoded using process model ontologies from semantic Web Service technologies (Yue et al., 2009), can be stored in RDF stores. More complex models can be built upon those existing models. This could benefit geospatial knowledge sharing and increase capabilities for geospatial feature discovery.

6. Conclusion and future work

This paper presents a workflow-based approach for discovery of complex geospatial features that uses geospatial semantics and services. Geospatial semantics, including both spatial and thematic semantics, can be employed in designing workflows. The task on discovering complex features in imagery is decomposed into a series of workflow steps computing spatial relations among elementary ground features in a specific geographic area. Workflows can be executed in a Web-based distributed environment by discovering features and spatial analysis services from a standard-compliant catalogue. The feature catalogue is designed to support the discovery of both feature instances and feature types. The case study on detecting schools and nuclear power plants demonstrates the applicability of the approach.

The results show that the location of complex features can be detected by locating one of its member features that follows the specific spatial relationships with other features. The workflow approach is helpful in formalizing computing steps for discovering different types of complex features. The use of service technologies brings the benefits of openness, dynamics, and interoperability.

Although an ontology example is provided for the case, it is neither complete nor intended to be interpreted by machine programs. Rather, it is only for the demonstration purpose and used for human interpretations. The workflow models in the paper are designed by humans based on knowledge contained in the ontology for complex features. It is possible to automate the modeling process using the ontologies for complex features. This could be done by introducing ontology-reasoning based task decomposition and planning for service composition. The future work will investigate this direction.

Acknowledgements

We are grateful to the anonymous reviewers for their valuable comments. Part of the work discussed in the paper was funded by U.S. Department of Energy (Grant #DE-NA0001123, PI: Prof. Liping Di), National Basic Research Program of China (2011CB707105), and Project 41271397 supported by NSFC. The authors would also like to thank Ms. Julia Di for editing and proofreading the manuscript.

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