Realizing Parameterless Automatic Classification of Remote Sensing Imagery Using Ontology Engineering and Cyberinfrastructure Techniques

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Abstract: It was an untouchable dream for remote sensing experts to realize total automatic image classification without inputting any parameter values. Experts usually spend hours and hours on tuning the input parameters of classification algorithms in order to obtain the best results. With the rapid development of knowledge engineering and Cyberinfrastructure, a lot of data processing and knowledge reasoning capabilities become online accessible, shareable and interoperable. Based on these recent improvements, this paper presents an idea of parameterless automatic classification which only requires an image and automatically outputs a labeled vector. No parameters and operations are needed from endpoint consumers. An approach is proposed to realize the idea. It adopts an ontology database to store the experiences of tuning values for classifiers. A sample

database is used to record training samples of image segments. Geoprocessing Web services are used as functionality blocks to finish basic classification steps. Workflow technology is involved to turn the overall image classification into a total automatic process. A Web-based prototypical system named PACS (Parameterless Automatic Classification System) is implemented. A number of images are fed into the system for evaluation purposes. The results show that the approach could automatically classify remote sensing images and have a fairly good average accuracy. It is indicated that the classified results will be more accurate if the two databases have higher quality. Once the experiences and samples in the databases are accumulated as many as an expert has, the approach should be able to get the results with similar quality to that a human expert can get. Since the approach is total automatic and parameterless, it can not only relieve remote sensing workers from the heavy and time-consuming parameter tuning work, but also significantly shorten the waiting time for consumers and facilitate them to engage in image classification activities. Currently, the approach is used only on high resolution optical three-band remote sensing imagery. The feasibility using the approach on other kinds of remote sensing images or involving additional bands in classification will be studied in future.

Keywords: parameterless automatic classification; ontology database; Cyberinfrastructure; remote sensing image classification; geoprocessing Web service; geoprocessing workflow.

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45 **1. Introduction**

46 After decades of studies on remote sensing image classification, researchers have
47 recognized that it is not an easy task to automatically and accurately classify the
48 image pixels [1-3]. Most of the current classification activities need a lot of human
49 intervention to find the best combination of input parameter values for the adopted
50 classification algorithms [4, 5]. For example, the artificial neural network (ANN)
51 based classification methods [6-8] usually require users to specify the number of
52 hidden layers, the number of neurons in each layer, the function on each neuron, the
53 initial weights of each border and training samples before every classification. Any
54 change on these parameters could lead to a completely different outcome. To obtain a
55 satisfying result, experts have to try a lot of possibilities to figure out a relatively
56 better combination. The finding process is very time consuming and full of
57 uncertainties. In the mean time, a combination of parameter values of an algorithm
58 might be only suitable for a particular image. Once the target image changes, the
59 combination need be reset too. Another thing that makes it worse is that even if the
60 same algorithm is applied upon the same image, different experts may get different
61 results. Because people, who have various preferences, have different definition about
62 “good result”.

63 Due to the heavy workload and uncertainties in pursuing for a good combination
64 of parameters, the work of classifying a remote sensing image seems very difficult to

be finished in a both automatic and accurate way. Most current researches still depend on traditional classification strategy with a lot of manual parameter tuning work that is greatly impacted by user preferences and costs too much labor and time. It remains a very big challenge to automate the whole classification process, remove the impact of human preference driven activities on the final results and reduce the overall workload and time cost.

This paper presents an idea of parameterless automatic classification trying to meet the challenge. Parameterless automatic classification requires only one image from consumers as input and outputs a labeled vector automatically. No adjusting parameters are needed. The whole process is a black box to endpoint consumers. An approach is proposed to realize the idea. It needs an ontology database to store the experiences on parameter tuning for various classification algorithms in many circumstances. The knowledge in the ontology database should be repeatedly tested and acknowledged [9]. The knowledge can help avoid remote sensing experts from repeating the time-consuming parameter tuning work on a new arriving image. A sample database is used to record training samples of image segments. Web services in Cyberinfrastructure [10, 11] are involved to supply the functionality to complete all the basic steps within each classification. Workflow technology is adopted to chain Web services together into a workflow instance that can be executed automatically. The values for the input parameters of each Web service are automatically selected from the knowledge database. The selection is driven by reasoning rules and target

image properties such as location, resolution, size, band count, camera, date, format, etc.

To validate the proposed approach, we implemented a Web-based prototypical system named PACS (short for **P**arameterless **A**utomatic **C**lassification **S**ystem). The knowledge database and sample database are currently built for high resolution (HR) and very high resolution (VHR) optical remote sensing images. So for now the system can only process three-band optical HR/VHR remote sensing images. Basically, the spatial resolution of HR optical images is between 1 and 10 meters (e.g., Geoeye-1 Blue/Green/Red, WorldView-2 Blue/Green/Yellow/Red, QuickBird-2 Blue/Green/Red, SPOT-5 PAN, IKONOS Blue/Green/Red, CBERS-2B PAN) while the spatial resolution of VHR optical images is less than 1 meter (e.g., Geoeye-1 PAN, WorldView PAN, Airbone, IKONOS PAN) [12].

A few images were tested on PACS. The results prove the feasibility of the proposed approach. It is indicated that the classified results will be more accurate if the two databases have higher quality. Once the experiences and samples in the databases accumulate into the same level as a human expert owns, the approach may get the results with similar quality to those produced manually.

The approach can bring a number of benefits to remote sensing image classification community. First, endpoint consumer only need submit an image and leave the technical components behind. The approach requires no parameter configuration and is totally automatic. Secondly, for remote sensing experts, their

work becomes easier as they do not have to make duplicated efforts on tuning input parameter values if the relevant experiences already exist in the database. On the other side, they can also contribute their experiences to augment the knowledge database. When other experts want to classify a new image with similar features, the knowledge will provide valuable references and help quickly obtain reliable classification results. Another benefit is that the approach makes it very possible to process the massively increasing amount remote sensing images in time. With the quick development of Earth observation sensors, the acquired remote sensing images are overwhelming everyday. Traditional manual image classification method is slow and can hardly discover the valuable information in most of the images in time, especially during an ongoing disaster such as earthquake, flood, typhoon, landslide, debris flow, etc. The proposed approach is automatic and parameterless so that the extra waiting time costs and possible error operations caused by human experts are eliminated. Thus, the approach provides a very good chance to match image processing capability with the massive increasing volume of images.

The remainder of the paper is organized as follows. Section 2 introduces the related work. In Section 3 an approach with three major modules is proposed. Section 4 implements PACS. Section 5 introduces some experiments conducted on the system and evaluates the approach based on the results. Section 6 discusses the pros and cons of the approach. Section 7 concludes the paper and gives the future work.

2. Related Work

Parameterless or automatic parameter tuning classification/clustering methods have been studied for decades in other domains such as mathematics [13-16], statistics clustering [17], medical science [18], biology [19], artificial intelligence [20-22], face recognition [23] and text detection [24]. For example, Foss and Zaiane [25] presented a parameterless clustering algorithm that clusters over a range of resolutions and finds a potential optimum clustering without requiring any parameter inputs. Chung et al [26] proposes an efficient and high performance parameterless quadrilateral-based algorithm for image segmentation. The experiment results show that the algorithm performs better than three other segmentation algorithms on over or under segmenting situation. Lezoray et al [27] introduced a parameterless discrete regularization framework and applied it in color image filtering. Pătrăucean et al [28] present a parameterless line segment and elliptical arc detector. Levachkine et al [29] proposed an approach to automatically interpret the semantics of image segments by low level image processing techniques. But these approaches are difficult to be directly transplanted to remote sensing domain due to the complexity, variety, uncertainty of the contained objects in remote sensing images.

In remote sensing domain, some researches have been conducted for automatic classification of geospatial objects like buildings, roads, lakes, rivers, forests, planes and cars from remote sensing imagery. Many attempts have been made but few substantial progresses were achieved. Benz et al [30] tried to use object oriented analysis combining with fuzzy methods to semi-automatically vectorize remote

sensing imagery and import the results into GIS (geographical information system).
Inglada [31] proposed an automatic recognition approach to discover man-made
objects in high resolution optical remote sensing images by using SVM classification
based on geometric image features. Sun et al [32] use spatial sparse coding
bag-of-words (BOW) model to detect targets with complex shape in high resolution
remote sensing images. Ren and Chang [33] developed a spectral-based algorithm for
automatic spectral target recognition (ASTR) in hyperspectral imagery with no
requirements on a priori knowledge. ASTR consists of two stage processes, automatic
target generation process (ATGP) and target classification process (TCP). The idea of
ASTR has been completely absorbed by object oriented classification theory. Ke and
Quackenbush [34] reviewed the major existing methods for automatic individual tree
crown detection and delineation from passive remote sensing. Hermosilla et al [35]
compared and evaluated two approaches for automatic building detection and
localization using high spatial resolution imagery and LiDAR data: threshold-based
and object-based classification. As they found, properly adjusted and adapted
parameters are required to obtain good results for both the approaches. Moranduzzo
and Melgani [36] presented a method to realize automatic car counting for unmanned
aerial vehicle images. Pardo-Pascual et al [37] presented a geometric method for
automated shoreline detection from Landsat TM and ETM+ imagery. Therefore, these
approaches have at least one tuning input parameter which requires users to adjust it
manually. In other words, the existing automatic methods are actually partially

automatic. A total automation classification approach, which takes an image and outputs a labeled vector, should be completely parameterless. Thus, this paper introduces the idea of parameterless automatic classification and a new approach to realize it based on the state-of-the-art techniques.

Another thing needed to be clarified is the difference between non-parametric classification [38] and parameterless classification. In remote sensing, most traditional classifiers, which depend on statistic assumptions like the multivariate normal distribution within spectral classes, are parametric [39]. But the assumptions cannot fit all the situations. In contrast, non-parametric classification methods are not limited by such assumptions [40]. Literally, non-parametric approaches including artificial neural networks (ANN) [6, 8, 41], CART regression tree [42, 43] and fuzzy logic [44, 45] are more suitable for remote sensing classification because of the variance and complexity of geospatial objects which hardly follow regular statistical patterns. So the major difference between parametric and non-parametric classification is whether it is based on statistic assumptions. In the mean time, non-parametric classification methods are not necessarily parameterless. Parameterless classification methods require no parameters from endpoint consumers and can be either parametric or non-parametric. Non-parametric classification and parameterless classification are defined from two different perspectives.

3. Methodology

To implement the idea of parameterless automatic classification, we propose an

approach consisting of three major modules: knowledge database, sample database and workflow management module (as shown in Fig. 1). They will be introduced in details below.

Figure 1. Flow chart of the proposed parameterless automatic classification approach

3.1 Knowledge Database for Automatic Parameter Tuning

Some initialization work need be done before classification. Two databases should be built first. One is a knowledge database which contains the experiences of optimal parameter combinations that have been repeatedly tested and acknowledged in real classification cases. A parameter combination usually fits a group of images with similar features. The mapping relationships between parameter combinations and tested images are stored in the database. We use semantic Web ontology language,

short as OWL, for the storage. Table 1 shows the topper ontology of parameter combination mapping relationships. An example snippet of the knowledge ontologies is shown in Table 2.

Table 1. The topper ontology of parameter combination mapping relationships

```

<?xml version="1.0"?>
<rdf:RDF
  xmlns="http://www3.csiss.gmu.edu/pacs/ontology/parameterrule.owl#"
  xmlns:rdf="http://www.w3.org/1999/02/22-rdf-syntax-ns#"
  xmlns:protege="http://protege.stanford.edu/plugins/owl/protege#"
  xmlns:owl="http://www.w3.org/2002/07/owl#"
  xmlns:xsd="http://www.w3.org/2001/XMLSchema#"
  xmlns:rdfs="http://www.w3.org/2000/01/rdf-schema#"
  xml:base="http://csiss.gmu.edu/pacs/ontology/parameterrule.owl">
  <owl:Ontology rdf:about="">
    <rdfs:seeAlso rdf:datatype="http://www.w3.org/2001/XMLSchema#string"
    >http://www3.csiss.gmu.edu/PACS</rdfs:seeAlso>
    <owl:versionInfo rdf:datatype="http://www.w3.org/2001/XMLSchema#string"
    >1.0.0</owl:versionInfo>
    <rdfs:comment xml:lang="en">This file defines the topper ontology containing rules for
    selecting appropriate values for input parameters of various classification methods.
  </rdfs:comment>
  </owl:Ontology>
  <owl:Class rdf:ID="Parameter_Value"/>
  <owl:Class rdf:ID="Input_Parameter"/>
  <owl:Class rdf:ID="Classification_Method"/>
  <owl:Class rdf:ID="Target_Image"/>
  <owl:Class rdf:ID="Selection_Rule"/>
  <owl:Class rdf:ID="Parameter_Configuration"/>
  <owl:Class rdf:ID="Parameter_Pair"/>
  <owl:ObjectProperty rdf:ID="has_configuration">
    <rdfs:domain rdf:resource="#Selection_Rule"/>
    <rdfs:range rdf:resource="#Parameter_Configuration"/>
  </owl:ObjectProperty>
  <owl:ObjectProperty rdf:ID="has_value">
    <rdfs:domain rdf:resource="#Parameter_Pair"/>
    <rdfs:range rdf:resource="#Parameter_Value"/>
  </owl:ObjectProperty>
  <owl:ObjectProperty rdf:ID="has_pair">
    <rdfs:range rdf:resource="#Parameter_Pair"/>

```

```

    <rdfs:domain rdf:resource="#Parameter_Configuration"/>
  </owl:ObjectProperty>
  <owl:ObjectProperty rdf:ID="has_parameter">
    <rdfs:domain rdf:resource="#Parameter_Pair"/>
    <rdfs:range rdf:resource="#Input_Parameter"/>
  </owl:ObjectProperty>
  <owl:DatatypeProperty rdf:ID="value">
    <rdfs:domain rdf:resource="#Parameter_Value"/>
  </owl:DatatypeProperty>
  <owl:FunctionalProperty rdf:ID="designed_for">
    <rdf:type rdf:resource="http://www.w3.org/2002/07/owl#ObjectProperty"/>
    <rdfs:range rdf:resource="#Target_Image"/>
    <rdfs:domain rdf:resource="#Selection_Rule"/>
  </owl:FunctionalProperty>
  <owl:FunctionalProperty rdf:ID="used_in">
    <rdfs:domain rdf:resource="#Selection_Rule"/>
    <rdfs:range rdf:resource="#Classification_Method"/>
    <rdf:type rdf:resource="http://www.w3.org/2002/07/owl#ObjectProperty"/>
  </owl:FunctionalProperty>
</rdf:RDF>

```

207

Table 2. A snippet of topper ontologies in knowledge database

```

<Selection_Rule rdf:ID="SelectionRule_14">
  <used_in>
    <Classification_Method rdf:ID="K_Nearest_Neighbor"/>
  </used_in>
  <designed_for>
    <Target_Image rdf:ID="TargetImage_15"/>
  </designed_for>
  <has_configuration>
    <Parameter_Configuration rdf:ID="ParameterConfiguration_16">
      <has_pair>
        <Parameter_Pair rdf:ID="ParameterPair_1">
          <has_parameter>
            <Input_Parameter rdf:ID="K"/>
          </has_parameter>
          <has_value>
            <Parameter_Value rdf:ID="5"/>
          </has_value>
        </Parameter_Pair>
      </has_pair>
    <Parameter_Pair rdf:ID="ParameterPair_2">

```

```

    <has_parameter>
      <Input_Parameter rdf:ID="allowUnclassified"/>
    </has_parameter>
    <has_value>
      <Parameter_Value rdf:ID="false"/>
    </has_value>
  </Parameter_Pair>
</has_pair>
... ..
</Parameter_Configuration>
... ..
</has_configuration>
</Selection_Rule>

```

208 If a new image has similar features with some image archived in the knowledge
209 database, the parameter combination of the image will be applied on the new image.
210 The similarity between two images is measured by the semantic distance between
211 their features in ontologies. Each image has a series of semantic properties like size,
212 scale, resolution, volume, format, projection, brightness, contrast, saturation,
213 bounding box, camera category, camera angle, sun height, spectral range, band
214 number, color encoding, picture date, etc. The semantic distance on each semantic
215 property is calculated and summed up by weight. The summed distance is regarded as
216 the overall semantic distance between two images. The equations of image similarity
217 (1) and semantic distance (2) are:

$$\text{Similarity}(A, B) = \frac{1}{\text{Dis}(A, B)} \quad (1)$$

$$\text{Dis}(A, B) = \sum \text{Dis}_i(A, B) \times \omega_i \quad (2)$$

220 where A and B are two remote sensing images, i means a semantic property, ω_i is the
221 weight for property i . $\text{Dis}_i(A, B)$ is equal to the shortest distance linking the property
222 i of A and B in ontologies. Commonly, the weight of location is larger than other

properties of images.

3.2 Sample Database for Automatic Supervised Classification

Sample database is built to record image segments as training sample for automating the supervised classification process. The samples are selected and uploaded by sophisticated experts via manual operation. Fig. 2 shows a Web interface used for sample selection. There are several basic principles which must be followed when selecting samples. The principles help ensure the sample database is accurate and consistent and prevent bad quality samples interfering and causing disastrous errors in classification results.

(1) Principle I: One object in one sample

This is the most important rule that experts must follow. Experts should guarantee there is no more than one object in each selected sample. For instance, a sample can not contain building and road at the same time. Besides, if a sample only covers a part of an object like a building, it is still qualified to this principle. The rule is easy to understand but very difficult to be enforced in real cases due to the complicated segments of Earth surface images. Generally, a sample in which the area of the major object takes more than 90 percent is also acceptable by a loosely constricted database.

(2) Principle II: Scattered selection

It means experts should select samples distributed all over the image rather than located in only one corner. This rule tries to make the selected samples to reflect all the possible characters of the objects in different locations. Take buildings as example.

The shape, structure and roof designs of the buildings in different places might be completely different. If only the buildings in one place are selected, the buildings in other places with different characters will be probably ignored and misclassified.

(3) Principle III: Medium size

The rule asks experts to select those samples with appropriate medium sizes. The specific explanation to this rule for different images might be various. Generally, the area of a sample should be bigger than one pixel and smaller than half of the image. Because it is hard to estimate the spatial characters of a sample if it is too small. Also, those samples whose lengths of interior and exterior boundaries are too long should be avoided. An image segment usually has very irregular shapes and patternless textual features when its boundary and area are too large. This rule has very flexible explanations and application scope.

Fig. 3 illustrates some samples registered in the database. Once a sample is approved, all the spatial, textual and spectral features of the sample will be calculated and stored [46]. Spatial features include area, border length, compactness, shape index, etc. Textual features include homogeneity, energy, entropy, contrast, etc. Spectral features include band mean value, band standard deviation, etc. The information that sample database stores contains the raw image segment, class name, feature values, registration date, original image URL, original segmented vector URL, feature id, owner, etc. The feature values of samples are pre- calculated during the registration so that the subsequent classification could directly use the values for time saving.

Figure 2. The interface for selecting and registering sample features

Previous Page Next Page 1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22				
Id	Data	Feature Id	Class	Actions
188		8960	Parking Lot	View Details Delete Edit
189		8968	Forest	View Details Delete Edit
190		8988	Forest	View Details Delete Edit
191		8990	Bare Land	View Details Delete Edit
192		5343	Building	View Details Delete Edit

Figure 3. Some registered samples

3.3 Workflow Management Module

Generally, there are four steps to be completed in the classification of a remote

sensing image: unsupervised classification, post process I, supervised classification and post process II. The unsupervised classification aims to cluster image pixels based on the features of themselves [47, 48]. The typical algorithms for unsupervised classification have ISODATA [49], k mean [50] and mean shift algorithm [51]. The experiment of this paper will use mean shift algorithm. Post process I is used to tailor the results of unsupervised classification to make them suitable for the usage of next step. Supervised classification aims to label the image clusters by semantic meanings [52-54]. Typical algorithms include KNN (K nearest neighbour) [55], Maximum Likelihood [56], SVM (Support Vector Machine) [31], ANN (Artificial Neural Network) [40], etc. The experiment of this paper will use KNN. Post process II adjusts and organizes the results of supervised classification to make them ready to use for endpoint consumers.

In this approach, each step is realized by a Web service and workflow technology is adopted to link and execute the Web services automatically. We build a workflow management module to integrate knowledge database, sample database and geoprocessing Web services together. Workflow management module supports the creation, execution, monitoring of workflow instances. Fig. 4 exhibits the interface creating a workflow for automatic classification. Geoprocessing Web services are listed on the left panel. Users can drag and drop the services into the right workspace panel and connect them by lines into a flow diagram. When the diagram is verified to be valid, a wizard will pop up and guide users to enter some information to finish the

workflow creation. The created workflow is deployed on an engine. Once a user inputs an image, a series of parameter values will be automatically selected according to the image based on the knowledge database and inputted to the deployed workflow. The workflow is activated and automatically executed and finally outputs a classification result.

Figure 4 Create a workflow for classification

4. Implementation

To validate the feasibility of the proposed approach, we implemented a Web-based prototypical system named PACS. The tools and libraries used in the development include GDAL, Geotools, JTS, GRASS GIS, OpenLayers API, MapServer WMS, Jena, MySQL, Apache Axis 2, Apache Tomcat 7.0, Protégé, Eclipse, BPELPower, Java Development Kit 1.7 (JDK), Linux Shell Script, g++, JavaScript, HTML5 and CSS3. The topper ontology of parameter tuning experiences is built by Protégé. Ontologies are stored through Jena in MySQL. The sample

database uses MySQL as database management system (DBMS) too. It now holds more than one thousand samples. Workflow engine uses BPELPower [47] that is developed by Center for Spatial Information Science and Systems in George Mason University. GDAL, Geotools, JTS, GRASS GIS are used to realize raster/vector data processing in geoprocessing Web services. Apache Axis 2 is used as Web service framework to build SOAP service interfaces. Apache Tomcat is used as Web container that holds all the geoprocessing services and PACS Web portal. Eclipse is an integrated development environment (IDE) for web developers. JDK, G++ and Shell are compilers and script language for compiling and linking program code into executables. JavaScript, HTML5 and CSS3 are used to build the Web pages of PACS.

Table 3. Algorithms and processes in PACS workflow

Workflow Step	Algorithm/Process
Unsupervised Classification	Mean Shift
Post Process I	Band Combination
	Small Polygon Removal
	Raster to Vector
Supervised Classification	KNN
Post Process II	Extra Area Elimination
	Same Classes Merging
	Splitting Classes into Different Layers

PACS has been published on the Web and the public URL is <http://www3.csiss.gmu.edu/PACS/>. The algorithms used in the implementation are listed in Table 3. Fig. 5 displays its two major interfaces. First it requires users to input an image by providing an URL or uploading from their computers. Click the button *classify* to begin. Once the classification is done, PACS will return the URL of the result vector. Within the process, PACS does not require any extra operation or

information from users. The classification is completely parameterless and automatically done. In addition, the Web page for viewing existing samples is: http://www3.csiss.gmu.edu/igfds/view_sample.jsp and the Web page for registering samples is: http://www3.csiss.gmu.edu/igfds/register_sample.jsp. The web services used in PACS mainly come from GeoBrain Web services (<http://geobrain.laits.gmu.edu/grassweb/manuals/index.html>). Two major URLs of accessing the services are <http://www3.csiss.gmu.edu/GeoprocessingWS/services> and <http://cube.csiss.gmu.edu/axis/servlet/AxisServlet>. The PACS workflow instance is implemented as a BPEL instance and deployed on BPELPower.

PACS is a prototype system and still has large room for improvements. For non-georeferenced images, result vectors may appear vertically flipped in GIS/RS software. Because the coordinate systems of displaying non-georeferenced vector and raster are vertically flipped in most software. This problem can be solved by reversing the non-georeferenced vectors using a web service (http://www3.csiss.gmu.edu/GeoprocessingWS/services/Vector_XAxisMirrorImage?wsdl).

The source code of PACS has been published in a public repository on the GitHub (<https://github.com/VirginiaJRS/PACS>). Any collaboration and contribution is welcomed and appreciated.

343

Figure 5. The interfaces of PACS

5. Experiment and Results

For evaluation purposes, we tested a number of images on PACS. Fig. 6 lists ten of them and Table 4 contains their detail information. The spatial resolution of the images ranges between 1 meter and 10 meters. Each image is followed by its classification result generated by PACS. In the results, the majority of geospatial objects like roads, buildings, trees, grasses and water bodies are recognized correctly. Some quantitative measurements on accuracy were conducted. We randomly selected sample segments from each image, compared their real land cover types with the classified types in the results and made an error matrix between them. Table 5 shows

the error matrix of image 1. The row represents real land cover types while the column represents classified land cover types. Based on the error matrix, a number of indices such as overall accuracy (OA) and Kappa coefficient (Kappa) [48] are calculated. OA is a ratio of the correctly classified pixels in all the sample pixels and its value is between 0 and 1.0. A larger value means the image has a higher accuracy. Kappa measures the agreement between the reality and the results from PACS and its value is less than 1.0. The formula of OA and Kappa can be found in [49]. Table 6 illustrates a statistic of the correctly and incorrectly classified sample pixels in the experiment. Fig. 7 shows the curves of OA and Kappa values of the classified results. Generally, if kappa is larger than 0.8, it means there is a very good agreement between the reality and the classification results. In Fig. 7, all the results, except image 5, 7 and 9, have kappa values bigger than 0.8. It reflects that PACS can classify high resolution remote sensing images with a fairly high accuracy. However, sometimes the accuracy of PACS results may be lower than its normal level such as image 1 whose kappa is 0.56 that represents only a moderate agreement. There are many reasons to the low agreement and some studies were done to discover them.

Particularly, the parking lots, load roads and air fields in image 2 are all classified as local roads. It is very difficult to distinguish them if they are smoothly connected and paved by the same materials. The boundaries among them are hardly visible in image 2. Boundary is very important and greatly affects the results in HR/VHR optical image classification. On the contrary, if the boundaries are clear and the

paving materials have different spectral reflectances like image 8, it will be much easier for PACS to separate them (e.g., image 8).

After carefully observing the results, the major reason for the low accuracy is that two image objects belonging to different classes have similar features. Two ways can be adopted to decrease the errors caused by this reason. One is to add new experiences or upgrade the existing experiences in knowledge database. New input parameter combination might improve the shape and granularity of image segments and increase the homogeneity among different kinds of objects so that it is easier for classifiers to differentiate them. Besides, the knowledge can also indicate which classifier is more suitable to classify the target image. Another way is to add more samples into the sample database. Classifiers can learn more detailed characters of the image objects based on a larger amount of samples so they may tell the minor differences between two similar kinds of objects.

For technical evaluation, the duration time of each processing is recorded and analyzed. Fig. 8 gives the curve of the ten test images. The wave is mainly effected by image volume and scale. The classification will take longer time if an image has bigger volume and scale. In Fig. 8, the classification of image 6 takes much longer than other images as it has the biggest dimension (width: 1638; height: 1090). Image 7 costs the least time as its size is the smallest (width: 300, height: 212). To make this approach operational in daily usage, improvements on both accuracy and speed must be studied further in next stage of work.

Table 4. The details about the test images

Id	Spatial Location	NO. of Bands	Resol- ution*	NO. of Classes	Time	Satellite	Pixel Size
1	-	3	5m	9	-	-	500x400
2	Dallas Love Field, TX	3	1m	9	2015	WorldView-2	800x540
3	Makati, Philippines	3	5m	9	2006	WorldView-2	600x480
4	Riyadh, Saudiarabia	3	3m	10	2012	Pléiades 1A	700x525
5	Madrid, Spain	3	3m	8	2014	WorldView-3	620x450
6	Pearl Harbor, HI	3	3m	9	2011	IKONOS	1638x1090
7	Olympic Park, Sydney, Australia	3	5m	10	2009	WorldView-2	300x212
8	Reliant Stadium, Houston, TX	3	3m	9	2008	QuickBird	800x510
9	-	3	5m	9	2015	-	746x521
10	Donbass Arena, Ukraine	3	3m	10	2012	SPOT	911x635
* The test images have been mosaiced and resolution is reduced from their original resolution. “-” means the image property is unknown.

Figure 6. Some results of parameterless automatic classification

Table 5. The error matrix of image A (unit: pixel)

	Real World Land Cover Type							
	Building	Bare Land	Local Road	Parking Lot	Yard	Grass	Field	Water
Building	6818	0	259	773	0	286	1048	0
Bare Land	0	0	0	0	0	0	0	0
Local	103	0	25441	0	0	0	0	0

Road								
Parking Lot	0	0	0	320	0	0	0	0
Yard	0	126	0	0	0	0	0	0
Grass	0	0	0	0	0	372	0	0
Field	0	0	0	0	0	0	0	0
Water	95	0	93	0	0	0	0	7793

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Table 6. Statistic of the sample pixels (unit: pixel)

Image	All	Right	Wrong
1	43527	40744	2783
2	313781	303238	10543
3	49597	46033	3564
4	134304	114960	19344
5	59303	39804	19499
6	735262	659692	75570
7	27675	22560	5115
8	166991	163722	3269
9	208946	170750	38196
10	187055	184215	2840

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Figure 7. The curves of measurement index of the results

Figure 8. The duration time of the classification of PACS

6. Discussion

This section discusses the advantages and disadvantages of this approach for different groups of users.

1) *Endpoint consumers*: PACS brings many benefits to general consumers who don't care about technical details behind classification. They are not interested in algorithms, parameters, band width, pixel size, feature space, training samples, etc and simply wish to get classification results directly with no extra operation. This is impossible when following traditional classification schemas, either supervised or unsupervised methods. PACS leverages ontology engineering to archiving classification experiences and cyberinfrastructure technique to performing automatic classification workflow. Algorithms and parameter values are automatically selected according to the features of target images. Web services are used to accomplish basic steps and connected into a workflow. The workflow can be executed by one single click. In the

overall process, there are no direct contact between endpoint consumers and technical components. The only thing endpoint consumers need do is to submit an image, wait for process accomplished and download result vector. The process can be looped many times by program to analyze tens of thousands of remote sensing images in one-stop manner. It can enable effortless and in-time classification on the rapidly growing amount of images acquired by thousands of sensors every day. On the other side, PACS is a black box and it is a little difficult for endpoint consumers to learn about the provenance of the results. This issue will be addressed in future by establishing a provenance storage and query service.

2) *Remote sensing experts*: PACS offers convenience to remote sensing experts and tries to make their lives easier. Experts spend a lot of time on choosing algorithms, tuning input parameters and selecting training samples for one image. For every new image, they have to repeat the selecting and tuning work. It is very time consuming and boring for human operators. However, PACS can store the previous success experiences and inference a set of algorithm and parameter values for each new image via ontology reasoning. If the experiences in PACS knowledge database accumulate as much as a sophisticated expert has, PACS should be able to automatically generate an optimal classification schema. For experts, their experiences are stored and reusable in future work so they don't have to repeat every time a new image arrives. The potential power of PACS will greatly save experts' time if the entire remote sensing classification community contributes experiences and samples to it. One

drawback is that the initialization of PACS needs many efforts on demonstrating the benefits and building trust in community members.

3) *Remote sensing service providers*: PACS could be considered as a revolution on service schema for remote sensing service providers. Traditionally, service providers classify remote sensing images and generate corresponding products first and then distribute them to consumers. The process may take weeks or even months according to the number of images and human workers' pace and working hours. The information value of remote sensing images will gradually decrease as time passes, especially in emergency scenarios such as earthquake, flood, blizzard, wide fire, and tornado. In PACS, consumers directly order classification products without assistance and the products are generated on-demand instantly and automatically. No direct human operation is needed from service providers during the whole process. PACS releases service providers from heavy burden on pre- generating classification results and assisting consumers to acquire and understand their products. However, the on-demand service requires very powerful processing and storing capabilities to deal with the large number of requests and huge volume of semifinished products. The greatly developed high-performance computing techniques like distributed computing, grid computing and cloud computing could relieve this burden.

7. Conclusion and Future Work

This paper presents a new idea about parameterlessly and automatically classifying remote sensing images and proposes an approach to realize it. The

approach integrates several state-of-the-art techniques like knowledge ontology database, Cyberinfrastructure Web services and geoprocessing workflow. The approach has three major modules. First, a knowledge database containing parameter tuning experiences is built. The knowledge database can relieve remote sensing experts from the heavy duties on repeatedly choosing appropriate classifiers and tuning parameters when new images arrive. Secondly, a sample database of image segments is created. The sample database helps turn supervised classification into an automatic process. The two databases provide the substantial conditions for parameterless automatic classification and must be finished in advance. Finally, a workflow composed of geoprocessing Web services is built. The input parameter values of each service are automatically reasoned from the knowledge database according to the features of the target image. The workflow can be automatically deployed and executed by a workflow engine. Once the three modules are available, a remote sensing image will be inputted to the workflow and the output will be a labeled vector annotating the contained polygons with land cover types. To evaluate the feasibility of the approach, we implemented a prototypical Web based system called PACS and made a number of experiments on it. The results show that the approach could automatically classify remote sensing images and have a fairly good average accuracy. The benefits brought by this approach include enhancing the current processing capability on the massively increasing remote sensing imagery, decreasing the errors caused by human preferences, relieving remote sensing experts

from heavy burden of repeatedly tuning classifier parameters and supervising classification, reducing the waiting time for the consumers of classification results and facilitating more people to easily mine valuable information from remote sensing images.

However, the results indicate that the approach may output a less accurate result if the two databases have little appropriate experiences and samples about an image. The quality of the results greatly depends on the quality of the knowledge database and sample database. The two databases need be continuously expanded to contain experiences and samples of more places in the globe. It is a huge project to build such two global databases. This research starts it and wishes more researchers could realize its long-term benefits and join in. In our next stage of work, some state-of-the-art techniques like big data storing and processing techniques will be used considering the huge volume of the databases. In addition, the feasibility of this approach in classifying or involving other kinds of remote sensing images, like high spectral images, elevation bands, LiDAR and SAR data, will be studied in future.

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