Geospatial Data Mining for National Security: Land Cover Classification and Semantic Grouping

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***Abstract*—Land cover classification for the evaluation of land cover changes over certain areas or time periods is crucial for geospatial modeling, environmental crisis evaluation and urban open space planning. Remotely sensed images of various spatial and spectral resolutions make it possible to classify land covers on the level of pixels. Semantic meanings of large regions consisting of hundreds of thousands of pixels cannot be revealed by discrete and individual pixel classes, but can be derived by integrating various groups of pixels using ontologies. This paper combines data of different resolutions for pixel classification by support vector classifiers, and proposes an efficient algorithm to group pixels based on classes of neighboring pixels. The algorithm is linear in the number of pixels of the target area, and is scalable to very large regions. It also re-evaluates imprecise classifications according to neighboring classes for region level semantic interpretations. Experiments on Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER) data of more than six million pixels show that the proposed approach achieves up to 99.8% cross validation accuracy and 89.25% test accuracy for pixel classification, and can effectively and efficiently group pixels to generate high level semantic concepts.**

I. INTRODUCTION

Data mining has been shown to have many applications in national security [11]. By mining data containing information about terrorists and their activities, it is possible to detect unusual and suspicious trends and patterns. More recently there has been much interest in mining multimedia data such as text, images, audio and video. For example, video surveillance data is being mined to detect suspicious events. Furthermore, mining data such as maps and related geographical data can help the analyst to determine whether there are unusual activities say in the middle of the desert or at some location. In this paper we will focus on one aspect of geospatial data mining. In particular, we will describe data mining algorithms for the classification of remote sensing data. Such classifications can be used to determine whether there are suspicious activities in particular regions.

Land cover information can be derived from various remote sensing systems, such as images from Landsat 7 ETM+, SPOT HRV/HRVIR, Terra ASTER and AVIRIS. The remote sensing images can have different spatial resolutions and spectral resolutions. Spatial resolutions range from 15m or less to hundreds meters [5], [14], while spectral bands range from 3 to more than 200 [10] due to different spectral wavelength ranges of sensors. Classification of image pixels by features from different spectral band data has been explored recently [5], [9], [14]. Yet these classifications use data of the same spatial resolution and similar spectral resolutions, and data of different spatial resolutions and different spectral resolutions have not been considered together for classification.

Classification on the pixel level cannot reveal semantic concepts at higher levels, and the semantic concepts at high levels can be crucial for security protection, environment evaluation and urban open space research. For instance, if a pixel or a few neighboring pixels are classified as water body, the location can be a pool in a residential area, a pond in an urban area, or a lake in a park or open rural area. Similarly, a group of buildings can be for public service in an urban area, for residential purpose in a residential area, or for highly confidential military use in a desert. It is of great need to develop high level concepts and distinguish them so that the semantic meanings of pixel classes become clear and accesses to some confidential concepts become controllable for security consideration.

This paper classifies data combined from different resolutions and forms high level concepts by grouping and re-evaluating classes of pixels. The classification is performed by using support vector machine (SVM) classifiers, which have been successfully demonstrated to outperform Maximum Likelihood (ML) and artificial neural network (ANN) classifiers [5], [9], [14]. By combining data of different resolutions, more discriminating capabilities can be achieved. Experiments show that less than 1% of ASTER data is needed for training, up to 99.8% cross validation accuracy and 89.25% test accuracy can be achieved, and training time can be tremendously reduced.

To generate high level concepts for a group of neighboring pixels, we will exploit ontologies. An ontology is a collection of concepts and their inter-relationships that collectively provide an abstract view of an application domain. We will develop domain-dependent ontologies as they provide for the specification of fine grained concepts while generic ontologies provide concepts in coarser grain [3], [6]–[8], [12].

Our grouping and re-evaluation algorithm considers local neighboring pixels for each pixel to generate high level concepts. Since only a limited number of neighboring pixels need to be considered for each pixel, tracking of classes of large

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neighboring regions can be avoided, making the algorithm feasible for groups of any large regions.

II. Related Work

SVM has demonstrated a competitive and powerful classification technique in land cover type classifications [5], [9], [14] among other applications. In [5], rural area land cover types are classified for a Thematic Mapper (TM) image of spatial resolution $28.5m$. SVM is compared with maximum likelihood classifiers (ML), artificial neural network classifiers (ANN), and decision tree classifiers (DT), and outperforms all the others statistically when enough features were used for classification. It also shows that the improvements due to the inclusion of four more TM bands exceeded those due to the use of better classification algorithms or increased training data size. This underlines the need to use as much information as possible in deriving land cover classification from satellite images.

Similarly, 7 vegetation types and 8 rural land cover types, are experimented with on multispectral (Landsat-7 ETM+) and hyperspectral (DAIS) data in [9], and SVM yields higher accuracy than ML and ANN.

Zhu and Blumberg [14] studied Urban open space classification using ASTER data from images of $15m$ and $30m$ resolutions respectively.

In contrast to the above work, our work combines data of different spatial resolutions, ie., data of $15m$, $30m$ and $90m$ spatial resolutions, for pixel classifications. The first three VIR bands with $15m$ spatial resolution, only cover the visible near infra-red portion of the spectrum. They are not sufficient for differentiating some of the urban features from each other, such as barren lands and concrete roads. The following six SWIR bands with $30m$ resolution and the five TIR bands with $90m$ resolution provide extra shortwave infra-red and thermal infra-red spectral information. All the images are resampled to $15m$ resolution so that the processing is conducted at the highest spatial resolution. The utilization of multi-resolution data provides better feature separability without sacrificing the spatial resolution of the raw image data. In addition to classification at the pixel level, this paper extracts high level concepts using ontologies, which reflect more general information than pixel level classes.

This paper studies not only the challenging urban area land cover classification at the pixel level, but also high level concepts which reveal more general information about a target area. The proposed efficient pixel grouping algorithm distinguishes this work from the above related work on land cover studies.

III. Classification of Image Pixels

Semantic concepts are to be developed from atomic classes at the pixel level, hence this section discusses ontologies first and then SVM for pixel classification, and finally the following section will discuss how to derive concepts from classes for large target areas as shown Figure 1.

Ontologies will facilitate the mining of information at various level of abstraction. For example, the concept, "Residential Area" can be further categorized into concepts House, Tree and Grass, etc. Here, the ontology will be represented as a directed acyclic graph (DAG). Each node in the DAG represents a concept. Interrelationships are represented by labeled arcs/links.

In our domain dependent ontologies first atomic concepts (e.g., water, house, building) will be identified based on spectral features of pixels using SVM. Next, using the ontologies and a set of atomic concepts we will infer a set of high level concepts for a set of regions (i.e., urban area, residential area and open area). For this, we will exploit ontology-based concept learning that improves the accuracy of the atomic concepts. It is possible that a particular target area may correspond to more than one concept which causes ambiguity and therefore, the disambiguation of the object is required [2]. Note that base, bat, glove may have several interpretations as individual terms, but when taken together, the intent is obviously a reference to baseball. The reference follows from the ability to determine a context/correlation for all the terms. For example, two adjacent areas may correspond to different concepts which may not co-exist according to ontologies. In this case, we can do pruning to get rid of irrelevant concepts.

Land cover types can be quite different at different places. At rural areas, vegetation might be the main land covers, while around big cities, vegetation covers would make way to buildings and grasses, etc. Suppose there are N land cover classes for a specific target area, samples at the pixel level are needed for each class in order to train the supervised classifiers.

SVMs are a class of learning machines that aim at finding optimal hyperplanes, the boundaries with the maximal margin of separation between every two classes, among different classes of input data or training data in a high dimensional feature space $\mathcal{F}$, and new test data can be classified using the separating hyperplanes.

Let $\{x_i, y_i\}$, $i = 1, 2, \ldots, L$ be L training data vectors x_i with class labels y_i, and $y_i \in \{-1, +1\}$ for binary classification. Given an input vector x, an SVM constructs a classifier of the form

$$g(x) = sign(\sum_{i=1}^{L} \alpha_i y_i K(x_i, x) + b)$$

where $\{\alpha_i\}$ are non-negative Lagrange multipliers each of which corresponds to an example from the training data, b is a bias constant, $\{y_i\}$ are the class assignments (-1 or +1) of training data vectors $\{x_i\}$, and $K(\cdot, \cdot)$ is a kernel satisfying the conditions of Mercer's theorem [13] and allows a dot product in a higher dimensional feature space to be computed in the input space. Frequently used kernel functions are the polynomial kernel $K(x_i, x_j) = (x_i \cdot x_j + 1)^d$ and Gaussian Radial Basis Function (RBF) $K(x_i, x_j) = e^{-|x_i - x_j|^2/2\sigma^2}$.

Support vectors are the closest points to the optimal hyperplane. After training, only the support vectors are used

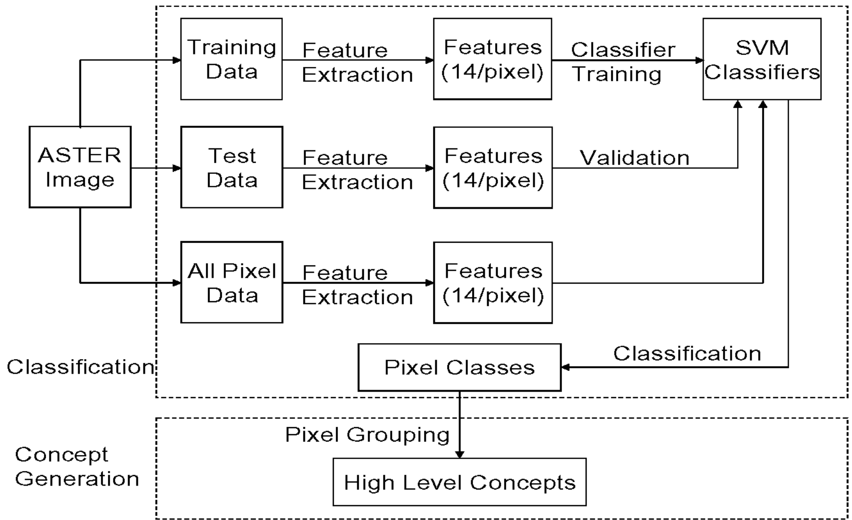


Fig. 1. The flow chart of concept generation

to define the optimal hyperplanes, and other training vectors have no influences. Since the non-support vectors do no affect margins and the optimal hyperplanes, they can be remove without any effects on the classifiers. This indicates that as long as points that are close to class boundaries are not missing, points that are far away from class boundaries can be removed, and SVM classifiers will not be affected. Hence, only a small number of samples are needed for training for those samples which are close to one another in the same class, and samples that vary in a class should be included for training. For example, due to different surfacing materials, such as asphalt and cement, roads in remote sensing images can be either bright or dark, making it necessary to include samples with different variations for training.

Multi-class classifiers are commonly constructed from binary classifiers because two-class problems are much easier to solve than multi-class problems. There are two approaches to using binary classes for multi-class classification: one-versus-one and one-versus-rest. The former constructs $k(k-1)/2$ binary classifiers for k classes, and each binary classifier is trained only on the data of the two involved classes. The latter constructs k binary SVM classifiers, and each classifier is trained with data from one class as positive examples and data from all the other classes as negative examples. It has been shown by experiments on large-scale problems in [4] that in general the accuracy rate of one-versus-one multi-class SVM is higher than that of one-versus-rest, and the training time of one-versus-one multi-class SVM is less than that needed for one-versus-rest classifiers. Due to these reasons, we chose to use the one-versus-one multi-class SVM classifiers for classification.

After classification of all pixels in the target area, only class information is available at the lowest level, and generating concepts at higher levels, such as residential areas or urban areas, etc., requires grouping of pixel classes as presented in the following section.

IV. Pixel Grouping for Semantic Concepts

Even if every pixel is correctly classified, high level concepts still cannot be obtained directly from individual pixels for certain specific location or region. Different high level concepts can share the same classes at the pixel level. For example, if we have grass and water body classes at the pixel level, and have high level concepts residential area and urban area, then both the concepts can have grass and water body at the pixel level. To derive high level concepts, pixel classes should be "merged" into high level concepts each of which covers multiple pixels. For simplicity, we refer to the low level atomic concepts as classes, and reserve the term concepts for the high level concepts derived from classes.

Various ways can be used to generate semantic concepts for target areas. One option is by area generation from pixels followed by high level concept assignment (AGHC). The other option is intermixing of area generation with labeling high level concept (IAGHC).

AGHC:

When grouping pixels, we can first assign each region of pixels of the same class a unique ID, find out neighboring regions for each region, and "merge" regions into high level concepts. Since regions of the same classes can be irregular and of different sizes, tracking the sizes and neighboring regions for region merge would be feasible for only small target areas. If a target area is very large, like the case in this study, there can be thousands of regions, and each region might have dozens of neighboring regions of different sizes. This makes it too time consuming or intractable to track neighboring regions of different sizes and to merge them for high level concepts.

IAGHC:

Instead of generating and merging neighboring regions of the same classes, we derive high level concepts directly from pixel classes by considering only neighboring pixels for each pixel.

Without loss of generality, let the target area have $row \times col$ pixels and the class labels of all $row \times col$ pixels be stored in a file with row rows and col columns. Let N_c be the number of high level concepts $C_1, C_2, \ldots, C_{N_c}$, and n_c be the number of classes $c_1, c_2, \ldots, c_{n_c}$ at the pixel level.

Although high level concepts can share some classes, they also have exclusive classes at the pixel level, as long as the number of pixels of these classes in a region is more than some threshold t_1. For example, the urban area should have pixels of the Building class at the pixel level, and the residential area should have "houses" at the pixel level, where "house" here refers to a possible combination of home, grass, tree or even water body for a pool due to low spatial resolutions. Some isolated buildings in a residential area or some houses in a urban area, due to physical presence of the actual classes or misclassification at the pixel level, can be considered to be "noises" and be "dissolved" into neighboring concepts by requiring a threshold t_2 of the number of pixels of the same class within a certain range.

Before discussing how to group pixels to derive high level concepts, let us define some terms as follows:

Definition 1: Signature class: the class c_i at a pixel p, which suggests a high level concept C_j at p without consideration of neighboring pixels.

For example, class Building could be the signature class of the Urban area concept, while class House would be the signature class of the Residential area concept. Note that no all classes are signature classes of some high level concepts. For instance, if we have a Grass class, it can be in multiple concepts, and would not be a signature class for any concepts (See Figure 4 for details).

Definition 2: NSET: the set of class labels or high level concepts of a pixel p and its k neighboring pixels.

Definition 3: Dominating class or concept: the signature class c_i or concept C_j in *NSET* which covers at least t_1 of the $k+1$ pixels, where t_1 is a threshold $\geq (k+1)/N_c$ and k is the number of neighboring pixels.

Definition 4: Let $\mathcal{D}$ be the number of instances of the dominating class or concept in *NSET*.

Definition 5: Isolated concept: A concept that covers only a small number t_2 of adjacent pixels, and is surrounded by other concepts. t_2 is a threshold and can be decided depending on how small a concept can be.

The pixel grouping algorithm as shown below first converts the class c_i of a pixel p into a high level concept C_j by the dominating signature class in the neighbor if the number of the dominating signature class is no less than a threshold t_1. Otherwise c_i of p remains unchanged during the first iteration. During the second iteration, the *isolated* concepts which cover only a small number of pixels are converted into neighboring concepts and any remaining raw pixel class is converted into a neighboring concept which has the dominating number of pixels in the neighbor.

The first iteration of step 1 is for converting c_i into the high level concept C_j if the number of the dominating signature class in $NSET$ (i.e., D) is no less than a threshold t_1 as in step 8. The second iteration of step 1 is for steps 11 and 14, which convert c_i or C_j into the dominating concept in $NSET$ respectively. Steps 2 and 3 are for each row and each column of pixels of the target area.

When the number k of neighboring pixels for a pixel p is fixed, each of steps 4, 5, 8, 11 and 14 take $O(1)$ time, hence the algorithm takes $O(n)$, where $n = row \times col$.

Figure 2 illustrates how to derive high level concepts from neighboring pixels. Four classes are shown as $c1, c2, c3$ and $c4$, and $C2$ and $C3$ are the concepts with respective signature classes $c2$ and $c3$. $k = 8$ for eight neighboring pixels and t_1 is 3 for the threshold of the first iteration. Initially the top left pixel is considered as shown in Figure 2(a). Since $c2$ is the dominating signature class, the concept for the pixel is assigned $C2$ as shown in Figure 2(b). Now the number of pixels of class $c2$ and concept $C2$ is 5 and dominating, the concept for the pixel considered is also $C2$ as shown in Figure 2(c). This process continues for all the pixels at the first iteration. The second iteration, not shown in the example, converts any remaining pixels, which are not converted in the first iteration due to non-dominating classes or concepts in the neighbors, and any isolated concepts into neighboring concepts.

V. Experiments with ASTER Data

The remote sensing data used in this study comes from ASTER images acquired on 31 December 2005. The target area covers the northern part of Dallas with the Dallas-Fort Worth International Airport located in the southwest of the image as shown in Figure 3. ASTER data covers visible through the thermal infrared regions of the electromagnetic spectrum, providing detailed information on surface temperature, emissive, reflectance, and elevation [1].

ASTER is a high performance optical sensor with 14 spectral bands, provides valuable scientific and practical data of the Earth for various fields of research. It is comprised of the following three radiometers:

VNIR (band 1 through band 3) stands for Visible and Near Infrared Radiometer which has a wavelength range of 0.56-$0.86 \mu m$.

SWIR (band 4 through band 9) stands for Short Wavelength Infrared Radiometer which has a wavelength range of 1.60-$2.43 \mu m$. In most cases only these bands are used to extract surface features.

TIR (band 10 through band 14) stands for Thermal Infrared Radiometer which covers 8.125-$11.65 \mu m$. This is important when research focuses on heat such as identifying mineral resources and observing atmospheric condition by taking advantage of their thermal infrared characteristics. By comparing with former widely used Landsat TM/ETM+, a representative

Algorithm 1: Pixel Grouping Algorithm.

for $iter = 1; iter++; iter <= 2$ **do**
  for $m = 1; m++; m <= row$ **do**
    for $n = 1; n++; n <= col$ **do**
      Let p be the pixel at (m, n), and let c_i be the class label at p and C_j be the concept at p if c_i has been converted into a concept;
      Update $NSET$ for p and find out $\mathcal{D}$ in $NSET$;
      if $iter$==*1* **then**
        if $\mathcal{D} >= t_1$ **then**
          Update c_i to the high level concept C_j associated with dominating signature class;
      else
        if c_i *is unchanged in previous iteration* **then**
          Update c_i to the high level concept C_j associated with dominating signature class;
        else
          if *Number of* $C_j \in NSET < t_2$ **then**
            Update the isolated concept C_j at p to dominating concept in $NSET$;

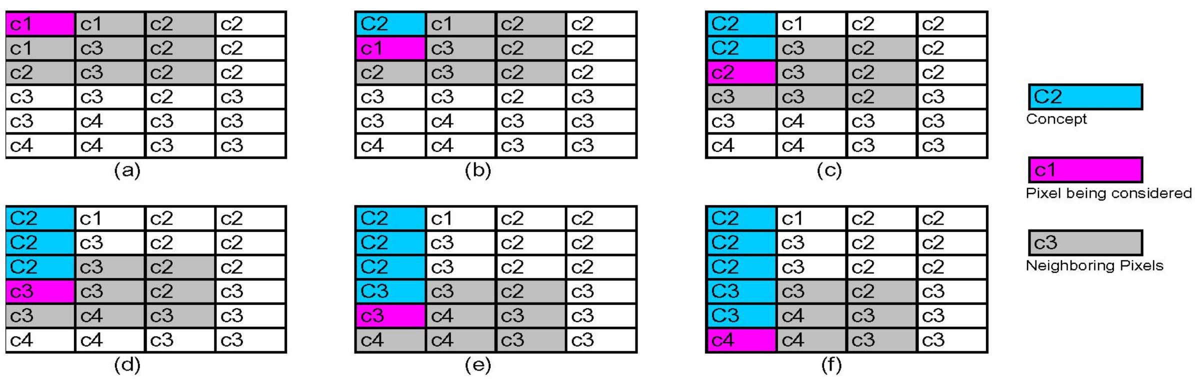


Fig. 2. An example of concept generation from pixel classes. The neighboring pixels are relaxed for boundary pixels as shown here.

earth observation sensor, ASTER can provide more information since they have 7 more bands.

The spatial resolution is $15m$ for band 1 through band 3, $30m$ for band 4 through band 9 and $90m$ for band 10 through band 14.

The target area covers 2319×2623 pixels, and we have 7 classes of land cover types at the pixel level: Water body, Barren land, Grass, Tree, Building and parking area, Road, and House. We have Road class separated from the Building and parking area class, because there are different land surfacing materials for roads, resulting in a large variation in road pixels. The House class is actually a mixture of home, grass, tree, road or even pool. There are 7079 training samples in total for the 7 classes, and the total number of samples for training is only about 0.11% of the whole target area.

As Figure 1 shows, after training SVM classifiers by cross validation with the training data, we tested the trained SVM classifiers with an independent test dataset, which is a small subset of the 2319×2623 pixels in the target area.

Samples of each class is randomly divided into 5 near equal size parts, and subsequently only one part is used for test, while the remaining 4 parts are used for SVM classifier training. We obtained cross validation accuracy of 99.8% as shown in Table I.

For independent test, we randomly chose another 9105 pixels. The overall accuracy is 89.25% as shown in Table I. The highest individual class accuracy is 100% for the Water class, and the lowest individual class accuracy is 75.26% for the Building class as shown in Table II. The confusion matrix (Table II) shows that the Road class and the Building class can be misclassified into each other. This is because some parking areas around buildings were considered to be in the Building class, which is very close to many highways in the target area. Some barren land areas are classified into the Grass class due to the fact that these areas are partially covered by grass according to high resolution images from Google Maps.

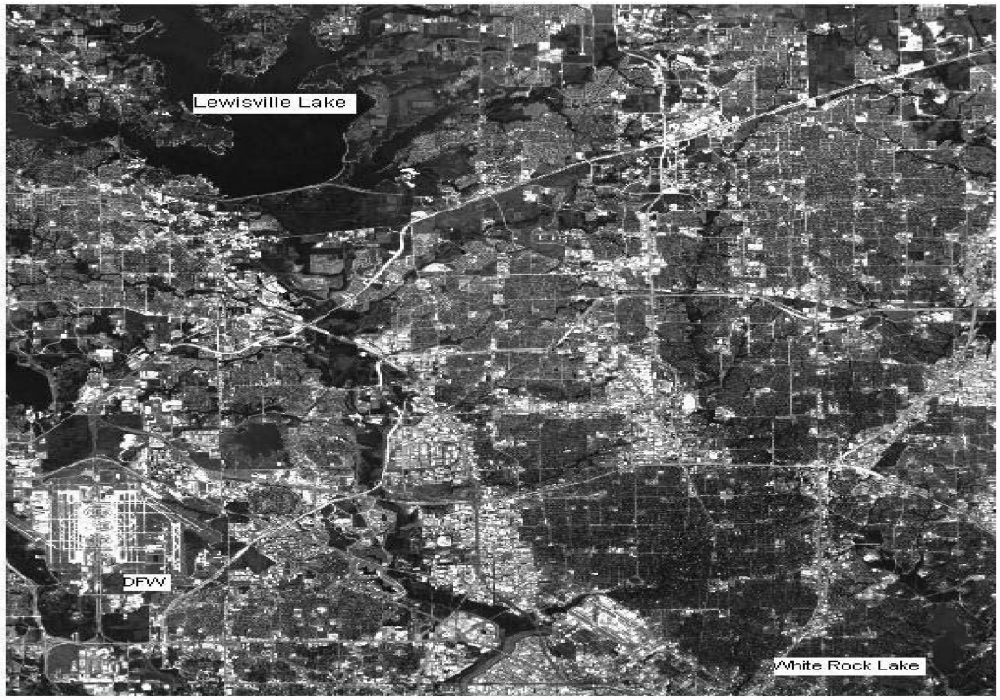


Fig. 3. The target area around the Dallas-Fort Worth (DFW) airport

TABLE I
TRAINING AND TEST PIXELS AND ACCURACY

	Water	Barren Land	Grass	Tree	Building	Road	House	Total	Accuracy(%)
Training	1175	1005	952	887	1041	435	1584	7079	99.8
Test	1898	1617	1331	1479	768	648	1364	9105	89.25

TABLE II
CONFUSION MATRIX FOR INDEPENDENT TEST DATA

Class	Predicted						
	Water	Barren Land	Grass	Tree	Building	Road	House
Water	1898	0	0	0	0	0	0
Barren Land	0	1225	216	0	143	33	0
Grass	0	15	1175	54	69	0	18
Tree	0	0	0	1454	0	0	25
Building	0	1	0	0	578	189	0
Road	0	0	0	0	143	500	5
House	0	0	0	0	9	59	1296
Accuracy	100.00	75.76	88.28	98.31	75.26	77.16	95.01

High level concepts are developed from pixel classes after all pixels in the target area have been classified. We have three high level concepts for the target area: Urban area (U), Residential area (R) and Open area (O) as shown in Figure 4. The signature class for Urban area is Building, the signature class for Residential area is House, and there are two signature classes for Open area: Water body and Barren land.

To develop concepts from classes, we considered eight directions for choosing the k neighboring pixels, where $k = 8, 24$, and 48 corresponding to the respective 2, 4, and 6 neighboring pixels at each of the horizontal and vertical directions. The threshold t_1 is set to 3, 9 and 17, the average number of pixels in the neighborhood for each concept. Figure 5 shows the distributions of three high level concepts in three representative regions of the target area. Figure 5(a), 5(d), and 5(g) are for the concept distributions around the Lewisville Lake at the Northwest of the target area. The lake is correctly identified to belong to the Open area concept, while some homes around the lake are identified to be in the Residential area. Figure 5(b), 5(e), and 5(h) are for the DFW Airport area at the Southwest of the target area. The shape of the airport is clearly identified to be the Urban area, while the large grass

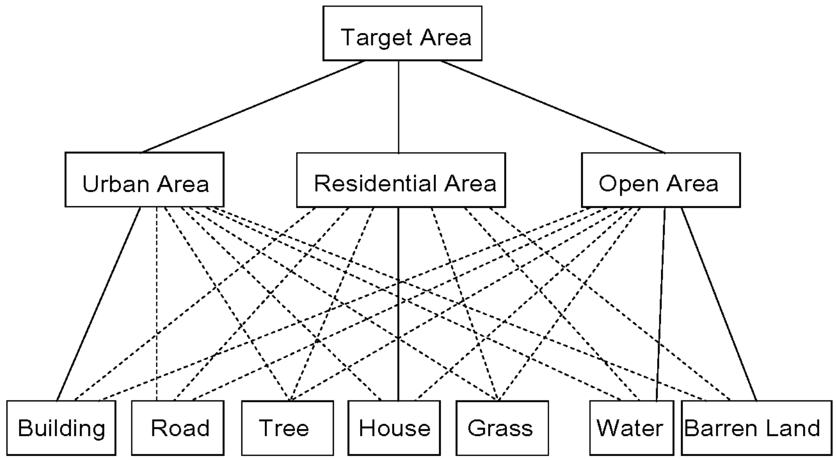


Fig. 4. Ontology of classes and concepts. Concepts and signature classes are connected with solid lines.

TABLE III
COMPUTATIONAL TIME FOR DIFFERENT NEIGHBOR SIZES

Pixels in neighbor	8	24	48
Time (seconds)	11.78	27.69	50.38

regions around the airport are identified to be the Open area. Figure 5(c), 5(f), and 5(i) are for the White Rock Lake area at the Southeast corner of the target area. This region is mainly the residential area due to the large amount of houses. The region is correctly assigned to the Residential area concept, and the White Rock Lake is also clearly labeled out.

Comparing the concepts developed at different neighbor sizes, we can find that when only 8 pixels are considered as neighboring pixels, more detailed information can be obtained, and the boundaries between different concepts are zigzagged. As more and more pixels are considered as neighboring pixels (i.e., $k = 24, 48$), classes are "filtered" by more neighboring pixels, and boundaries become more and more smoothed.

Table III lists the computational time in seconds. When 9 pixels (a pixel and its 8 neighbors) are considered, less than 12 seconds are needed. When more neighboring pixels are considered, a little more time is needed for the increased pixels, yet the computational time is still less than one minute for the case of 48 neighboring pixels. It is clear that proposed pixel grouping algorithm is very efficient.

VI. Conclusions

This paper studies the urban area land cover types based on SVM classification of ASTER data, and develops high level concepts from the pixel classes, or atomic concepts.

The target area has 7 class types: Water body, Barren land, Grass, Tree, Building, Road, and House. We extracted three high level concepts from these 7 classes: Open Area, Urban Area and Residential Area. Some of the classes are signature classes of high level concepts, others are not. For example, Water bodies and Barren land are signature classes of Open Area, Building is the signature class of Urban Area, while House is the signature class of Residential Area.

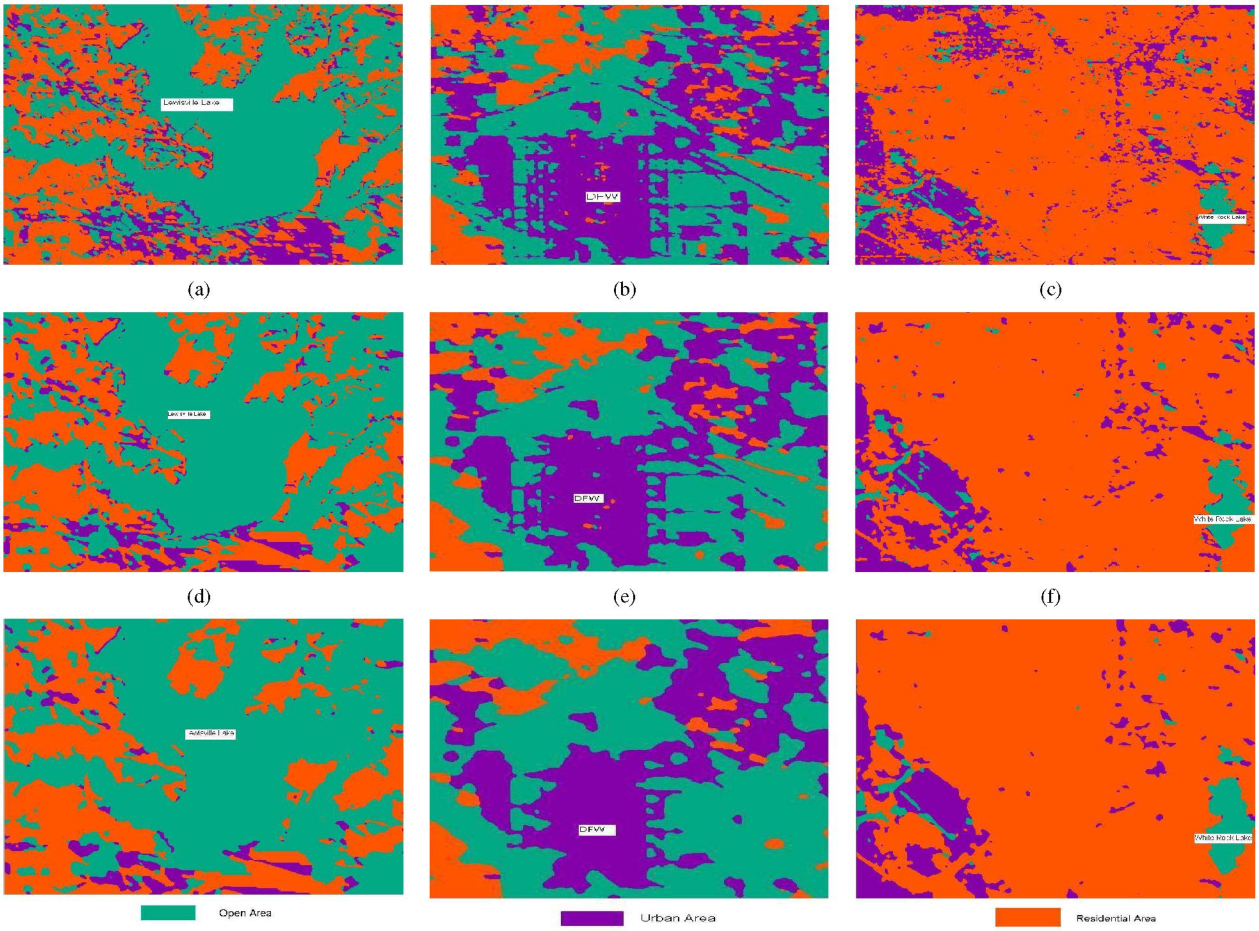
Experiments show that 99.8% cross validation accuracy can be obtained for training data of 7 classes, and 89.25% test accuracy can be achieved for independent test data. The high classification accuracy provides a good ground for high level concept development.

An efficient concept generation algorithm has been proposed. The algorithm converts a pixel class into the dominating concept in the neighboring area during the first iteration, and converts remaining pixel classes and isolated concepts into neighboring concepts in the second iteration. Different neighbor sizes have been experimented with, all generate correct concepts at large scale. The algorithm is linear in the number of pixels, and takes less than a minute for our target area of more than 6 million pixels.

High level concepts as developed in this paper provide more general information at a large area than pixel classes, and provide highly semantic guides for land cover studies and national security.

This work can be extended in several ways. More high level concepts can be added for different semantic considerations, or some of the current three concepts can be divided into less general concepts. Other classifiers can also be explored for classification to improve the accuracies of individual classes, such as Building and Barren Land. Improvement of signature classes are especially important to high level concept development. Ontology-based concept learning can be further investigated to improve accuracy of high level concepts.

Our research has many applications including for climate change detection, suspicious event detection and various other GIS applications. As we have discussed earlier, our main goal



(a) (b) (c)

(d) (e) (f)

(g) (h) (i)

Fig. 5. High level concepts at different locations: (a), (d) and (g) around the Lewisville Lake, (b), (e) and (h) around the DFW Airport, and (c), (f) and (i) around the White Rock Lake. Neighboring pixels $k = 8$ for (a), (b), and (c); $k = 24$ for (d), (e), and (f); $k = 48$ for (g), (h), and (i).

is to apply geospatial data mining techniques for national security applications. Classifying high level concepts as well as extracting the semantic content is a significant step towards detecting unusual activities and suspicious regions.

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