A Vector Agent-Based Unsupervised Image Classification for High Spatial Resolution Satellite Imagery

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Abstract

Conventional unsupervised methods only use the digital numbers (DNs) of pixels to classify an image in feature space. In this context, these methods lack the necessary abilities to address the issues, such as mixed pixels or spectral similarity between clusters. This paper presents a new approach based on Geographic Vector Agents (GVAs) for unsupervised image classification of High Spatial Resolution (HSR) satellite image. GVAs are objects that can construct their own geometry and interact spatially with other objects in the context of Geographic Automata System (GAS). This structure enables GVAs to capture the spectral information of each cluster through a set of polygons in the spatial space. The spectral information of these polygons (e.g., covariance) allows to GVAs to apply a classifier algorithm such as Maximum Likelihood (ML) to classify an image more accurate compared to the classical unsupervised algorithms. The preliminary results show the high capabilities of GVAs to classify HSR satellite image.

Keywords: Geographical Vector Agents, GVA, GAS, High Spatial Resolution, unsupervised image classification.

1. Introduction

In a remote sensing context, image classification refers to the process which converts a set of pixels into a number of classes or meaningful objects. By considering pixels as the underlying unit for image classification, there are two types of classification: supervised and unsupervised. In the former case, supervised methods use training data to classify an image. As the process requires human input, it can be time consuming, difficult and expensive (Chi et al., 2008), except where there is a simplistic structure or a finite number of classes.

In contrast, unsupervised or clustering methods simply use the spectral reflectance of the pixels to classify an image. In this regard, an analyst only determines the number of clusters. Accordingly, unsupervised methods do not require as much intervention (Tso and Olson, 2005) and priori information (Duda et al., 2001) to classify an image, compared to supervised approaches. As the procedure requires a minimal amount of human input, it is more attractive (Tso and Olson, 2005) and also efficient especially where there is not sufficient information about the classified objects, or we need the high degree of automation to classify an image.

1.1 Methods and limitations

In the context of a conventional unsupervised method, we usually use an iterative technique, such as k-means algorithm or Iterative Self-organizing Data Analysis Techniques Algorithm (ISODATA), to classify an image. Such approaches consider pixels in isolation to cluster pixels in a dataset only based on statistics. This means that, these methods cannot perceive and use the contextual information that might exist between pixels in spatial space.

To address this limitation, Tso and Olsen (2005) used the Hidden Markov Model (HMM) to take advantage spectral and contextual information of pixels to implement a clustering process. Kirnidis and Chatzis (2010) reduced the effect of the noise in terms of c-means technique through the use of spatial information and gray level of pixels. Zheng et al. (2014) showed that the use of spatial and spectral information can improve the robustness and noise insensitiveness of the conventional fuzzy c-means (FCM) to classify high spatial resolution imagery.

In spite of these efforts, most of these algorithms have addressed the contextual information through a local window around a candidate pixel in terms of a conventional clustering method, such as c-mans. These methods lack the necessary abilities to address an irregular and dynamic geometry for considering the neighboring pixels of the candidate pixel in spatial space.

1.2 Proposed method

In the proposed method, first, we use a set of dynamic objects, namely vector agents (VAs), which can find and change their own geometry and classes.

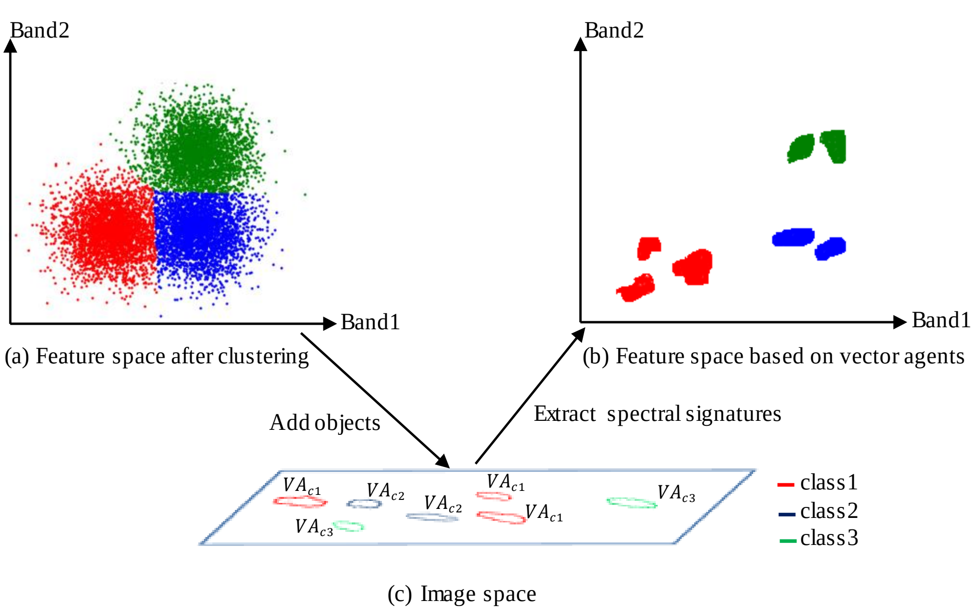


Figure 1. (a) and (b) display initial and updated feature space. (c) shows the distribution of VAs in spatial space.

These objects can communicate with each other and their environment to find and extract their own shape and class in spatial space even where the objects have different classes (Figure 1c). In fact, these objects enable a conventional unsupervised method, such as k-means, to redefine a new feature space (Figure 1b) based on a set of new spectral signatures of the initial clusters. In the next stage, these signatures are used by a classifier, such as Maximum Likelihood (ML), to reclassify the remaining pixels in the feature space.

2. Vector Agents

In general, the VA is a distinct type of Geographic Automata (GA); a processing mechanism which is characterized by states, transition rules, location, location rules, neighbourhood and neighbourhood rules (Torrens et al., 2005). Hammam et al., (2007) and Moore (2011) defined and implemented the elements of VAs for an urban and agricultural scenario, respectively. Borna et al., (2014) defined the elements of VAs for an image classification process (equation 1).

$$\mathbf{GA} \sim (\mathbf{K}; \mathbf{S}, \mathbf{T_S}; \mathbf{L}, \mathbf{M_L}; \mathbf{N}, \mathbf{R_N}), \quad (1)$$

where:

- **K** defines the automata types which are regarded as evolutionary, static, and elastic objects (Goodchild et al., 2007).

- $\mathbf{T_S}$ rules enable automata to update their own state, namely **S**. State and transition rules are formulated in terms of ML and Support Vector Machines (SVMs).

$$\mathbf{T_S}: (\mathbf{S_t}, \mathbf{L_t}, \mathbf{N_t}) \rightarrow \mathbf{S_{t+1}} \quad (2)$$

- $\mathbf{M_L}$ rules and methods enable the automata's geometry to constantly evolve. VAs used a directional planar graph in the context of a winged-edged data structure.

$$\mathbf{M_L}: (\mathbf{S_t}, \mathbf{L_t}, \mathbf{N_t}) \rightarrow \mathbf{L_{t+1}} \quad (3)$$

- **N,** $\mathbf{R_N}$ is the pair of terms that defines the VA's neighbourhood and its relations with it based on the Euclidean distance between VAs in spatial space.

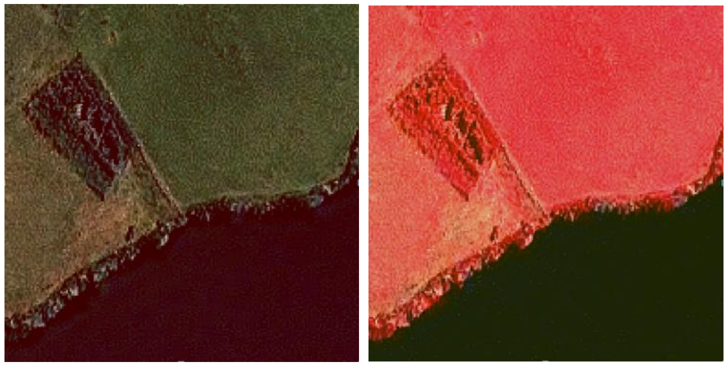
$$\mathbf{R_N}: (\mathbf{S_t}, \mathbf{L_t}, \mathbf{N_t}) \rightarrow \mathbf{N_{t+1}} \quad (4)$$

This mechanism enables each object to dynamically update itself based on its state, geometry and neighbours in image space.

3. Experimental Results

The experimental results of the proposed approach are based on a multispectral IKONOS image (Figure 2). This image was taken from a rural area of Dunedin placed in the South

Island of New Zealand with 1m x 1m pixel size which is obtained from an image fusion process.



(a) (b)

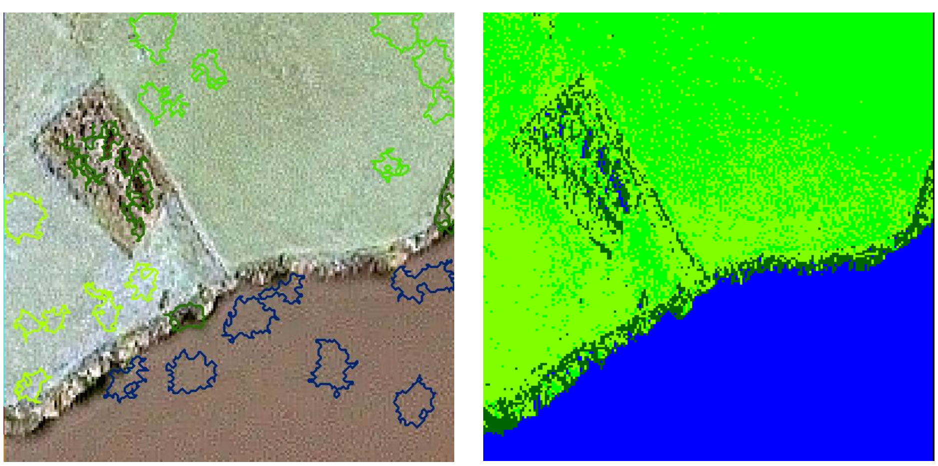
Figure 2. Subset image of a multispectral IKONOS satellite image: true colour composite (a) and false colour composite (b).

First, we use the k-means clustering method specified based on 4 different classes (Figure 2a). After the initial clustering process, the covariance matrix of each cluster is computed based on the pixels that can satisfy the following equation.

$$\overline{\rho_i} - z \times \sigma_{\rho,i} < \rho_{c,i} < \overline{\rho_i} + z \times \sigma_{\rho,i} \,, \quad (5)$$

where $\overline{\rho_i}$ and $\sigma_{\rho,i}$ are the mean reflectance and standard deviation in band i of all pixels in each cluster, respectively. z is a constant set to 1 in this case.

The simulation starts by initialising a desired number of VAs with a nondeterministic shape boundary. In this event, VAs use the above covariance matrix to find their initial classes. This process is automatically and randomly performed in a vector space. After that, VAs use the embedded rules to find, change and extract their shapes and classes (Figure 3a).



(a) (b)

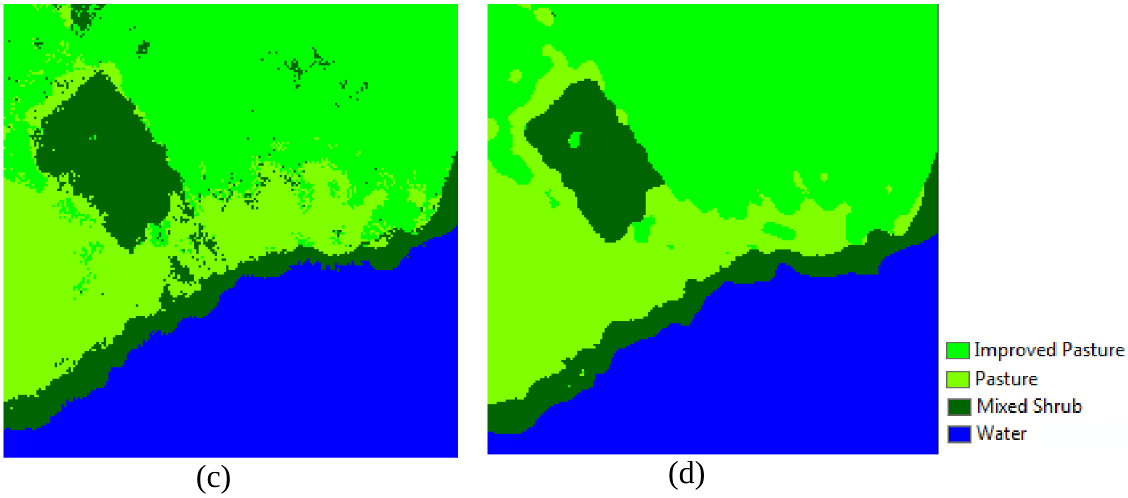


Figure 3. Spatial distribution of VAs (a). classified images in terms of k-mean**s** (b), VA (c) and ML supervised algorithms (d).

In the next stage, a classifier agent uses the spectral information of VAs to reclassify the remaining pixels in feature space (Figure 3c). Table 1 shows the accuracy of the proposed method compared to the conventional k-means method. To evaluate the accuracy of VA-based method, the result of ML supervised algorithm is also applied (Figure 3d).

Table 1. Number of samples, producer's accuracy, overall accuracy, and kappa coefficient of the scenario 1.

Class	**K-means**	**VA-based**	**Supervised-ML**
Improved Pasture	85.71%	85.71%	92.86%
Pasture	83.33%	91.67%	100%
Mixed Shrub	71.43%	100.00%	85.71%
Water	100.00%	100.00%	100.00%
Overall accuracy	85.71%	91.07%	94.64%
Kappa coefficient	0.788	0.869	0.920

4. Conclusions

This paper presents a new unsupervised approach to cluster very high spatial resolution imagery based on VAs. Experimental results demonstrate the capabilities of VAs to improve the accuracy of the conventional clustering method by incorporating the spatial information into spectral data. The use of a primary clustering algorithm, which has potential to offer the optimum number of the clusters, can increase the accuracy of the classified image to achieve a fully automatic image classification.

5. References

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