

Agile Segmentation and Classification for Hyper Spectral Image Using Harris Corner Detector



Chemistry

KEYWORDS : Neural network, Harris corner detector, classification

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ABSTRACT

A set of high-resolution remote sensing images covering multiple spatial features, we propose an classification based on unsupervised technique including pixel-wise and sub-pixel-wise methods to detect possible built-up areas from remote sensing images. The motivation behind is that the frequently recurring appearance patterns or repeated textures corresponding to common objects of interest in the input image data set can help us distinguish built-up areas from other features. In our proposed method have two main steps First, extract a large set of corners from each input image by an improved Harris corner detector. In the second step we incorporate the extracted corners into a likelihood function to locate candidate regions in input image. Experimental results demonstrated that the proposed approach have got accurate estimation compare to the existing algorithms in terms of detection accuracy.

INTRODUCTION

A multispectral image consists of several bands of data. For visual display, each band of the image may be displayed one band at a time as a grey scale image, or in combination of three bands at a time as a color composite image. Interpretation of a multispectral color composite image will require the knowledge of the spectral reflectance signature of the targets in the scene. Remote sensing has become an important source of land use/cover information at a range of spatial and temporal scales [3]. Traditional classification techniques assign every pixel to a single class, but remote-sensing images, particularly at coarse spatial resolutions, are commonly dominated by mixed pixels that contain more than one class on the ground [4]. To obtain the sub pixel information, soft classification techniques and spectral un mixing algorithms have been used to obtain the fraction of each class in a pixel [5]–[7]. However, the sub pixel spatial attribution of the different classes in a pixel will still be unknown with these techniques Quantitative measurements of the spectral characteristics of materials using a remote sensing system having greater than 60 spectral bands with a spectral resolution less than 10 nm producing a contiguous portion of the light spectrum which defines the chemical composition of the material through its spectral signature Hyper spectral sensing allows the analyst to perform reflectance or fluorescence spectroscopy on each spatial element (pixel) of the image scene.

This can sometimes involve distinguishing targets from very similar backgrounds, or locating examples of targets that are smaller than the nominal pixel size. Therefore unsupervised classification (back propagation) has been used. Back propagation is the generalization of the Windrow-Hoff learning rule to multiple-layer networks and nonlinear differentiable transfer functions. Input vectors and the corresponding target vectors are used to train a network until it can approximate a function, associate input vectors with specific output vectors, or classify input vectors in an appropriate way as defined by you.

With the development of remote sensing technologies, high-resolution remote sensing images have become critical sources of information in diverse fields such as geography, cartography, surveillance, city planning, and soon. Among them, monitoring the distribution, growth, and characteristics of built-up area receives a growing number of attentions for it can greatly help local agency to update land maps and draw city plans. In such applications, the basic but important step is to extract built-up regions from the high-resolution remote sensing images .Generally, a built-up area represents a vital and highly dynamic environment which is mostly composed of both manmade and natural objects. Because the texture of the scene is distinct from that

of the natural scene, major approaches for built-up area detection are based on texture analysis.. Its application for built-up region detection can be found. In their later work, a build up area presence index is proposed for built-up area extraction in panchromatic satellite image, which is based on fuzzy rule-based composition of anisotropic texture co-occurrence measures.

In recent years, built-up area detection based on local invariant features has revealed promising results. In developing a method to detect built-up areas and buildings in very high resolution Ikonos satellite images based on scale-invariant feature transform features and graph theory. However, it needs some template building images for training and therefore suffers from a high computing complexity and memory requirement. In their later, a more direct method is used. However, since it solely depends on local features for recognition, it can often be too weak of a signal to reliably detect the built-up regions in complex satellite image

2. RELATED WORK

2.1 Sub pixel Mapping

Most of the proposed methods were pixel-based. These methods try to estimate the probability of each pixel to belong to the possible classes by employing statistic measures based only on spectral properties. The Maximum Likelihood Classification (MaxVer) [16] remains one of the most popular methods for RSI classification. MaxVer computes the probability of each pixel to belong to each of the defined classes and uses that information to assign the class with the highest probability. The improvements in sensor technologies have increased the accessibility to high-resolution images.

As a result, new approaches have been developed to make a better use of the available data. This led to researches that take into account the neighborhood of the pixels in the analysis and, thus, texture features in the classification of RSIs. In [17], a general overview of RSI classification until 2005 is presented. That work discusses the challenges and describes all the steps that compose the classification process. Various classification methods are presented and grouped according to its taxonomy. More recently, a new trend can be observed. Many studies [18–21] consider information encoded in regions (group of pixels) for RSI classification tasks. Gigantic et al. [18] proposed a classification algorithm for high resolution RSIs, combining non-supervised and supervised classification strategies



Fig. 1 .Proposed System Architecture

In this method, regions were classified by using Mahalanobis distance and Support Vector Machines (SVM). Lee et al. [19] created a region-based classification method for high resolution images that exploited two approaches: MaxVer with region means and MaxVer with Gaussian Probability Density Function. Both works presented better results than pixel-based classifiers. Yu et al. [20] also proposed a method to classify RSIs based on regions. The image segmentation and classification were performed by using fractal networks and non-parametric K-Nearest Neighbor (KNN), respectively. Another recent work in this research area was developed by Katartzis et al. [21] who proposed a region-based RSI classification method that uses Hierarchical Markov Models.

The key issue in sub pixel mapping is how to determine an optimal sub pixel distribution of each class in a pixel. Spatial dependence, as proposed by Atkinson in 1997, inspired from Tobler’s first law [10], is the universal criterion, which refers to the tendency for spatially proximate observations of a given property to be more alike than more distant observations [9]. A coarser fraction image is obtained by a spectral un mixing technique, as the input image and each pixel is divided into \times sub pixels, where S represents the scale factor. The number of sub pixels for each land-cover class is then determined by the abundances of the fraction image. Fig. 2 illustrates the principle of sub pixel mapping and describes a simple example with two classes. In the fraction image, as shown in Fig. 2(a), assuming the scale fraction S is 4, a coarse pixel is divided into 16 (4×4) sub pixels, and 0.5 in the fraction image means that 8 (16×0.5) sub pixels belong to land-cover class 1. Fig. 2(b) and (c) describe two possible distributions of sub pixels, and the former is superior to the latter, with higher spatial dependence.

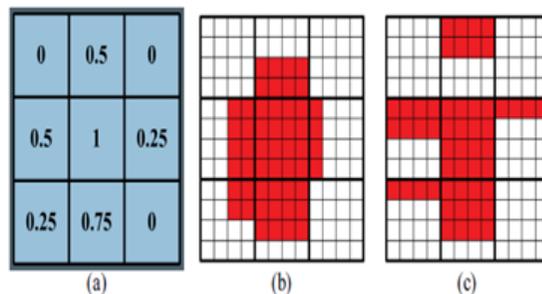
Generally speaking, four kinds of features can be utilized in image processing: low-level visual features, local features, local-global features and biologically inspired features [11], [12]. However, these features are always based on the assumption that all pixels in the image are pure pixels, which is unreasonable in remotely sensed images. Fisher [13] suggested that there are four types of mixed pixels in remotely sensed images as follows [14].

- 1) Small sub pixel objects: the size of the object is smaller than the size of the pixel.
- 2) Boundary pixels: the sizes of two or more land-cover classes on the ground may be larger than the sizes of the pixel, but parts of their boundaries lie in a single pixel.
- 3) Intergrade pixels: a pixel allocates a space for a transition

from a cluster of one class to a cluster of another class.

- 4) Linear sub pixels: the length of a land-cover class maybe longer than a pixel but its width is thinner, and the land-cover class runs through a pixel. Many sub pixel mapping methods have been proposed to tackle the different types of mixed pixels: sub pixel objects [15],

Fig. 2. Image of 3×3 coarse pixels and possible distributions (scale = 4, 2classes). (a) Fraction image. (b) Optimal distribution. (c) Inferior distribution.



Sub pixel mapping techniques aim to determine the optimal distribution of sub pixels of the different land-cover classes within a pixel, based on the fraction images. The fractions of each category can be obtained by a spectral un mixing technique. Sub pixel mapping can transform the fraction image into a map of suitable sub pixel locations for the different classes within a pixel. Each pixel can be divided into a number of sub pixels during this transformation, according to the predefined scale S and the abundances of the fraction image.

2.2 Harris Corners :

The Harris Corners module identifies corners present within the image using the Harris Corner detection technique. The technique first identifies vertical and horizontal edges using a Sobel type edge detector. Those edges are then blurred to reduce the effect of any image noise. The resulting edges are then combined together to form an energy map that contains peaks and valleys. The peaks indicate the presence of a corner. Without loss of generality, we will assume a greyscale 2-dimensional image is used. Let this image be given by I . Consider taking an image patch over the area (u,v) and shifting it by (x,y) . The weighted sum of squared differences (SSD) between these two patches, denoted S is given by

$$S(x,y) = \sum \sum w(u,v) (I(u+x,v+y) - I(u,v))^2 \quad (1)$$

$u \ v$

Corners as Interest Points:

Many applications require relating two or more images in order to extract information from them. For example, if two successive frames in a video sequence taken from a moving camera can be related, it is possible to extract information regarding the depth of objects in the environment and the speed of the camera. The brute force method of comparing every pixel in the two images is computationally prohibitive for the majority of applications. Intuitively, one can image relating two images by matching only locations in the image that are in some way interesting.

Such points are referred to as interest points and are located using an interest point detector. Finding a relationship between images is then performed using only these points. This drastically reduces the required computation time.

Requirements of a Corner Detector

It is desirable for a corner detector to satisfy a number of

criteria:

1. All “true corners” should be detected.
2. No “false corners” should be detected.
3. Corner points should be well localized.
4. Detector should have a high repeatability rate (good stability).
5. Detector should be robust with respect to noise.
6. Detector should be computationally efficient.

The detection of all true corners with no false corners is application (interpretation) dependent since there is no well defined definition of a grayscale corner. However, in many images the corners are intuitively clear and such images can be used to evaluate the performance of different corner detectors (see Evaluating and Comparing Corner Detectors). Localization refers to how accurately the position of a corner is found. This is critical in applications requiring the precise alignment of multiple images (for example, in registration of medical images). In Figure 1.2 the reported position of the corner is illustrated with a red circle. The corner detector on the right has good localization

Whereas the corner detector on the left has poor localization. Although good localization is desirable for all applications, it is not critical for all applications (for example, an object detection algorithm may simply require the approximate location of all the object’s corners).

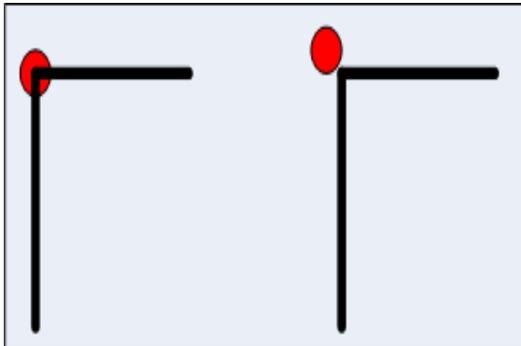


Fig .3. Illustration of good and poor localization, respectively

3. ARCHITECTURE OF THE NEURAL NETWORKS:

An Artificial Neural Network (ANN) is an information processing paradigm that is inspired by the way biological nervous systems, such as the brain, process information. The key element of this paradigm is the novel structure of the information processing system. It is composed of a large number of highly interconnected processing elements (neurons) working in unison to solve specific problems. ANNs, like people, learn by example. An ANN is configured for a specific application, such as pattern recognition or data classification, through a learning process. Learning in biological systems involves adjustments to the synaptic connections that exist between the neurons.

A three-layer network was used. The input layer consisted of nine neurons, corresponding to a central pixel and its eight surrounding neighbors. This implied that sub pixels could not be calculated for border pixels, as part of the information about their surroundings was missing. The input values were the membership values of these pixels for a certain class. The (unknown) spatial configuration was assumed equal for all classes. Consequently, the network was trained using membership values regardless of their originating class. In this way, only one network for all classes had to be trained, instead of having to train a separate network for each land cover class. The number of neurons in the hidden layer was set at 15.

In this training algorithm, an input pattern is first preoperated through the network in the so-called feed-forward phase. Afterward the difference between the calculated and the desired output is back-propagated from the output neurons to the first layer of the network, thereby adjusting the network weights in the opposite direction of the derivative of the network error with respect to each individual network weight. The learning rate was set at 0.1, and a momentum coefficient of 0.2 was applied.

Back propagation is a popular algorithm employed for training multilayer connectionist learning systems with nonlinear activation functions (sigmoid). However, its drawback has been partly attributed to the following: (1) there are some flat-spot problem regions, where the derivative of the sigmoid activation function approaches zero, and the weight changes become negligible; (2) because the gradient descent algorithm is used here, the constructed high-resolution image is not very good, as indented shapes appear in the boundary, which makes the algorithm inefficient. To resolve this problem, an observation model is introduced in every fraction image after the Back propagation.

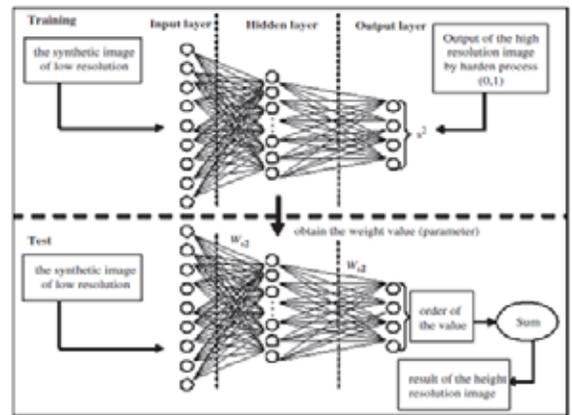


Fig .4. Architecture of Neural network

4. EXPERIMENTAL RESULT:



Fig .5. a) Feature Detection



Fig. 5. b) object Detection

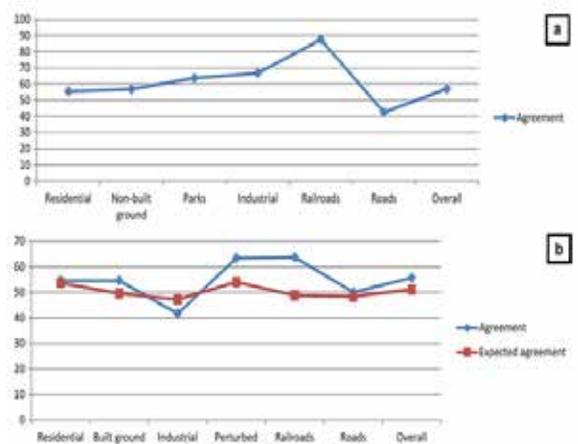


Fig. 6. Kappa index of agreement between observed and predicted common ragweed for various habitat: (a) in Montreal; (b) in Valleyfield.

5. CONCLUSION

A novel adaptive sub pixel mapping method based on a back propagation model and a winner-take-all class determination strategy namely Harris corner, has been proposed to adaptively deal with hyper spectral images by using original image down sampling and spectral un mixing to meet with the real situation. Harris corner utilizes a back propagation model, which has the ability to regularize the ill-posed problem by adding prior information to obtain a better sub pixel mapping result. The traditional sub pixel mapping algorithms always utilize the fraction image obtained by the classification image down sampling method as the input information. In Harris corner, the original image down sampling and spectral unmixing results is applied to acquire the sub pixel mapping result. Since the determination of the regularization parameter is very difficult, the traditional methods usually set a series of values to find the best result. In addition, the sensitivity analysis of the regularization parameter λ demonstrates that Harris corner obtains similar results to the optimal parameters of manual selection and hence provides an effective sub pixel mapping method for hyper spectral remote sensing imagery.

REFERENCE

[1] J. M. Bioucas-Dias et al., Hyper spectral remote sensing data analysis and future challenges," IEEE Geosci. Remote Sens. Mag., vol. 1, no. 2, pp. 6–36, Jun. 2013. | [2] J. M. Bioucas-Dias et al., Hyperspectralunmixing overview: Geometrical, statistical, and sparse regression-based approaches," IEEE J. Sel. Topics Appl. Earth Observ. Remote Sens., vol. 5, no. 2, pp. 354–379, Apr. 2012. | [3] G. G. Wilkinson, "Results and implications of a study of fifteen years of satellite image classification experiments," IEEE Trans. Geosci. Remote Sens., vol. 43, no. 3, pp. 433–440, Mar. 2005. | [4] G. M. Foody, "Hard and soft classifications by a neural network with a non-exhaustively defined set of classes," Int. J. Remote Sens., vol. 23, no. 18, pp. 3853–3864, Jan. 2002. | [5] X. Ceamanos, S. Douté, B. Luo, F. Schmidt, G. Jouannic, and J. Chansot, "Intercomparison and validation of techniques for spectral unmixing of hyper spectral images: A planetary case study," IEEE Trans. Geosci. Remote Sens., vol. 49, no. 11, pp. 4341–4358, Nov. 2011. | [6] R. Heylen, D. Burazerovic, and P. Scheunders, "Fully constrained least squares spectral unmixing by simplex projection," IEEE Trans. Geosci. Remote Sens., vol. 49, no. 11, pp. 4112–4122, Nov. 2011. | [7] M.-D. Iordache, J. Bioucas-Dias, and A. Plaza, "Sparse unmixing of hyperspectral data," IEEE Trans. Geosci. Remote Sens., vol. 49, no. 6, pp. 2014–2039, Jun. 2011. | [8] A. J. Tatem, H. G. Lewis, P. Atkinson, and M. S. Nixon, "Super resolutiontarget identification from remotely sensed images using a Hopfield neural network," IEEE Trans. Geosci. Remote Sens., vol. 39, no. 4, pp. 781–796, Apr. 2001. | [9] P. M. Atkinson, "Mapping sub-pixel boundaries from remotely sensed images," Innovations in GIS IV. London, U.K.: Taylor & Francis, 1997, ch. 12, pp. 166–180. | [10] W. R. Tobler, "A computer movie simulating urban growth in the Detroit region," Econom. Geograph., vol. 46, pp. 234–240, Jun. 1970. | [11] D. Song and D. Tao, "Biologically inspired feature manifold for scene classification," IEEE Trans. Image Process., vol. 19, no. 1, pp. 174–184, Jan. 2010. | [12] K. Huang, D. Tao, Y. Yuan, X. Li, and T. Tan, "Biologically inspired features for scene classification in video surveillance," IEEE Trans.Syst. Man, Cybern. Part B, Cybern., vol. 41, no. 1, pp. 307–313, Feb. 2011. | [13] P. Fisher, "The pixel: A snare and a delusion," Int. J. Remote Sens., vol. 18, no. 3, pp. 679–685, Feb. 1997. | [14] A. M. Muad, "Super resolution mapping," Ph.D. dissertation, School Geography, Univ. Nottingham, U.K., 2011. | [15] A. M. Muad and G. M. Foody, "Super-resolution mapping of lakes from imagery with a coarse spatial and fine temporal resolution," Int. J. Appl.EarthObserv. Geoinf., vol. 15, pp. 79–91, Apr. 2012. | [16] R. Showengetrd, Techniques for Image Processing and Classification in Remote Sensing, New York: Academic Press, 1983. | [17] D. Lu and Q. Weng, "A survey of image classification methods and techniques for improving classification performance," International Journal of Remote Sensing, vol. 28, no. 5, pp. 823–870, 2007. | [18] X. Gigandet, M. Cudra, A. Pointet, L. Cammoun, R. Caloz, and J.-P. Thiran, "Region-based satellite image classification: method and validation," ICIP 2005., vol. 3, pp. III–832–5, September 2005. | [19] J. Lee and T. A. Warner, "Image classification with a region based approach in high spatial resolution imagery," in International Archives of Photogrammetry, Remote Sensing and Spatial Inf. Sciences, Istanbul, Turkey, July 2004, pp. 181–187. | [20] Q. Yu, P. Gong, N. Clinton, G. Biging, M. Kelly, and D. Schirokauer, "Object-based detailed vegetation classification with airborne high spatial resolution remote sensing imagery," Photogrammetric Engineering Remote Sensing, vol. 72, no. 7, pp. 799–811, 2006. | [21] A. Katartzis, I. Vanhamel, and H. Sahli, "A hierarchical markovian model for multiscale region-based classification of vector-valued images," IEEE Transactions on Geoscience and Remote Sensing, vol. 43, no. 3, pp. 548–558, March 2005. | [22] L. Zhang, K. Wu, Y. Zhong, and P. Li, "A new sub-pixel mapping algorithm based on a BP neural network with an observation model," Neurocomputing, vol. 71, no. 10–12, pp. 2046–2054, Jun. 2008. | [23] Roland Ngom And Pierre Gosselin "Development of a remote sensing-based method to map likelihood of common ragweed (ambrosia artemisiifolia) presence in urban areas" IEEE journal of selected topics in applied earth observations and remote sensing, vol. 7, no. 1, january 2014