Journal of Geomatics

Vol 8 No. 2 October 2014

Enhancing object boundaries by subpixel mapping of satellite image

Arun Kumar Rai and Kamal Jain
Civil Engineering Department, Indian Institute of Technology Roorkee, India
Email: raiarun89@gmail.com

(Received: Jun 23, 2014; in final form: Oct 07, 2014)

Abstract: Object detection of earth surface using remote sensing images has a great use in military operations and other change detection applications. Objects occur at both pixel and subpixel level i.e. it accomplishes some pure pixels and some mixed pixels. Mixed pixel generally occurs near the boundary of objects. Pure pixel is not of great concern but mixed pixel cause a great degree of uncertainty in information extraction of information from remote sensing data. Mixed pixel is pixel constituting of more than one class. Hard classification process allocate pixel with the class having highest proportion. Soft classification provides proportion of class at a particular pixel but it fails to provide the spatial arrangement of subpixels within a pixel that results in degradation in quality of object boundary. In this paper object boundary has been intensified using a superresolution algorithm which improves spatial distribution of subpixel classes by considering attractiveness to neighboring pixel as decision criteria. Results showed that targets can be identified in image more easily and accurately.

Keywords: Subpixel classification, Subpixel mapping, Object detection, Super resolution

1. Introduction

With the advancement in remote sensing technology, the information derived from remote sensing images is gaining its applicability in area of environment monitoring, resource management, disaster management etc. A wide range of remote sensing data in terms of spatial, spectral and temporal resolution is available in recent time. Extraction of accurate and precise information is the requirement of user community. So design of accurate and efficient algorithm for processing remote sensing data is required.

A major application of remote sensing images includes land use land cover information extraction and object detection. Information extraction procedures are used for change detection studies where as object detection methods are applied in military applications and in structural engineering applications. With the availability of high spectral resolution data an object of interest is easy to resolve spectrally but it may not be spatially resolved, especially at object boundaries, due to presence of mixed pixel.

Pure pixel is a pixel representing one spectral class. Mixed pixel comprises of more than one spectral class. Mixed pixel contains intermediate reflectance characteristics of spectral classes present in instantaneous field of view. Mixed pixel is a great source of uncertainty. Object boundary constitutes large amount of mixed pixel. Hard classification allocates a mixed pixel to the class having highest proportion, resulting in loss of information. Soft classification overcomes this problem by providing the fraction of spectral class in the pixel but the spatial arrangement of subpixels is lost causing dizziness at object boundaries.

To overcome such problems, subpixel mapping technique was introduced. Many researchers proposed various algorithms on different parameters which are discussed in subsequent section. The main limitations with these methods were random allocation of subpixels and recursive optimization procedure which are time consuming.

In this paper, a subpixel mapping algorithm is discussed which uses nonrandom initial allocation of subpixel. It adopts non-recursive optimization technique for increasing spatial dependence. The algorithm relies on intensifying object at or near the boundaries.

2. Literature review

Subpixel mapping was proposed by Atkinson (1997) in which image pixel was fragmented into subpixels. Then each subpixel was allocated to a class. The spatial arrangement of subpixel was then manipulated for all subpixel with a view to increasing spatial attraction. Subpixel mapping is also termed as superresolution mapping in remote sensing literature (Aitkinson, 2009). Super resolution algorithms aim to maximize spatial dependencies. According to first law of geography, the near things are more alike than things that are further apart (Tatum et al., 1970a).

Various subpixel mapping techniques are proposed by researchers and some important are briefly discussed below. Boucher and Kyriakidis (2006) grouped subpixel mapping in two categories. The methods in first group enhance spatial dependence between the pixel and subpixels. Second group of algorithms uses some knowledge base for performing subpixel mapping.

Tatem et al. (2001a) proposed a knowledge based procedure in which pixel was split into subpixels. Proposed algorithm initially classifies the image then boundary features were used for training. The algorithm is then applied on whole image to get super resolution mapping (Verhoeye and De Wulf, 2002).

Colorimetry, the numerical specification of the color of visual stimuli, is related to the spectral sensitivities of the three cone photoreceptors. Colorimetry is more intuitive when defined in terms of cone excitations than when defined in terms of imaginary primaries, such as the CIE XYZ primaries. Color-matching data and color matching functions (CMF) tell us which spectral distributions will match under a given set of viewing conditions for a given observer. However, they tell little about the actual color appearance of the match, which can vary enormously with the viewing conditions. It has been quantitatively evaluated and outperforms the classical gray world algorithm (Suresh and Jain, 2013 a-d; 2014). As a future research they plan to improve the multi domain analysis that drives the automatic white balancing, considering more features, related to objects whose reflectance have the most perceptual impact on the human visual system, such as urban, vegetation or sky. They also intend to introduce the influence of the device in the illuminant estimation, investigating the role of the sensor profiling (Suresh and Jain, 2013 a-d; 2014).

Verhoeye and De Wulf (2002) proposed a procedure in which they formulated the subpixel mapping as a linear optimization problem. Priority was given to closer pixel as compared to pixel that is far away (Tatum et al., 2001b). Many feed forward neural network based algorithms were proposed. Hopfield neural network based method was used by Tatem et al. (2001a) where first network was trained to identify location of subpixel. The method was employed on whole image to perform super resolution. The Hopfield neural network is designed as 2D lattice which is representation of image. The input is provided to neuron by corresponding image subpixel. First the algorithm was developed for binary image (Tatum et al., 2001b) later on it was extended to estimate land cover patches using variogram with some prior information (Muada and Foody, 2010). However in Hopfield neural network based technique addition information is required as input to network for example data obtained using light detection and ranging (LIDAR). Apart from this temporal data has been added to improve accuracy (Kasetkasem et al., 2005).

A neural network predicted wavelet coefficient based method was proposed Tatem et al. (2001b). The technique expresses the spatial dependence as a function of wavelet coefficients. To evaluate wavelet coefficient neural network was trained a 3X3 pixel window was fed to train a feed forward back propagation network. The major disadvantage of this technique is training requirement of large set of data. Markov random field based approach was used which include contextual information for generating super resolution land cover map (Kasetkasem et al., 2005). In this technique, it is assumed that every map follows a Markov property. However model was unable to handle isolated pixels. A pixel swapping based technique proposed for binary case (Atkinson, 2009). The conventional super resolution algorithms have a problem of random initial allocation of subpixel and recursive optimization procedure which time consuming (Boucher and Kyriakidis, 2006). They proposed a super resolution technique which uses Geostatistics based measures as prior information. The method requires only single image, the algorithm is non-iterative and fast.

3. Methodology

The proposed method identifies the object in remote sensing image and then the object boundary are enhances by mapping subpixel to its appropriate location. Fractional maps obtained from subpixel classification are provided as input to the super resolution mapping algorithm. Overall process for enhancing object boundary is presented in figure1.

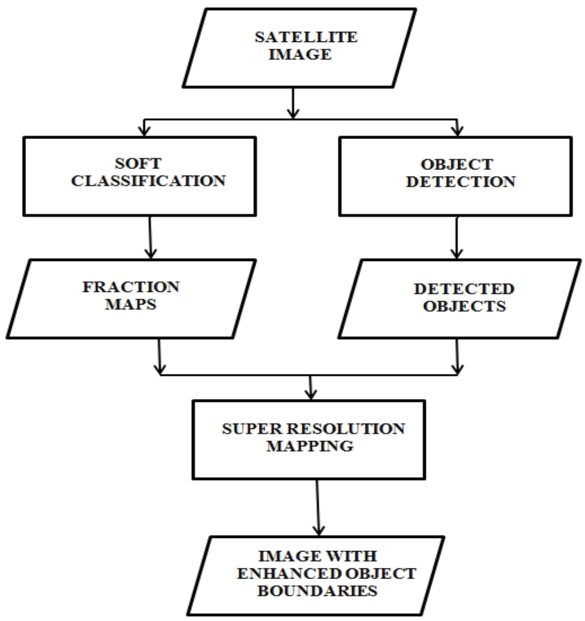

Figure 1: Overall process for object enhancement

The proposed method for enhancing the object boundary aims to maximize the spatial dependency based on principle that near things are more alike. For enhancing the object boundary the satellite image are soft classified to provide fractional abundance of classes within each pixel. The output is series of fractional images equivalent to number of classes present in the image. The soft classified fraction images are provided as input to super resolution mapping process which maps the subpixel of mixed pixels to most appropriate location which depends on their attractiveness to neighboring pixel.

Simultaneously objects are also identified whose output is also provided to the super resolution process as additional information. The overall process can be divided in following steps. Subpixel classification process is available in most of commercial digital image processing software like ENVI. Here a subpixel mapping is used for boundary enhancement. The following steps are involved in subpixel mapping process.

- Achieving abundance values
- Defining window of interest
- Defining scale factor.
- Calculating distance between subpixel and neighboring subpixels
- Initial allocation of classes to subpixel based on attractiveness
- Correcting multiple and non-allocated pixels

(1) Achieving fraction abundances

The fractional images image can be obtained from various techniques like linear mixture model, fuzzy c-mean classifier, maximum likelihood classifier, neural network or SVM based methods. The fraction images contain the abundance value of a class at particular pixel. Soft classification technique provides the proportion of class in a pixel, but it fails to provide the spatial distribution of these classes. As a result, there is haziness in the output image at object boundaries. A 3x3 image subset with obtained fraction map for class A and B is shown in figure 2.

100%	100%	25%
100%	50%	0%
75%	0%	0%

(a)

0%	0%	75%
0%	50%	100%
25%	100%	100%

(b)

Figure 2: Fraction maps obtained using soft classification (a) class A (b) class B

(2) Defining window of interest

Window of interest defines the number of neighborhood pixel that is to be considered for calculating the attractiveness of a class to a subpixel. The window size affects the accuracy of classification procedure so it is required to be considered. Figure 3 shows a 3x3 neighborhood consideration.

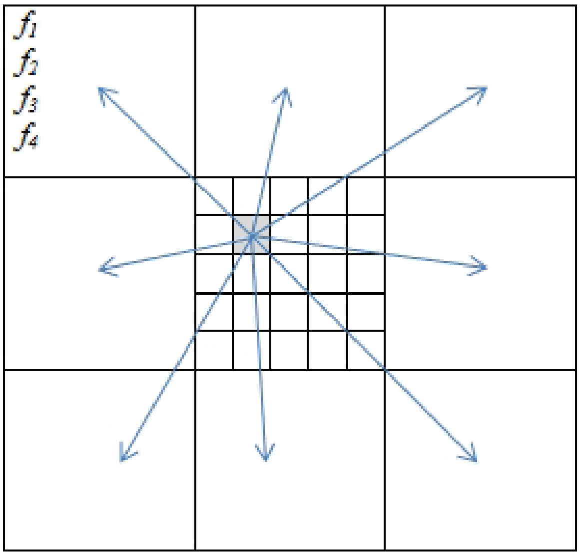

Figure 3: A 3X3 neighborhood window for calculating attractiveness

(3) Defining the scale factor

Scale factor defines the number of subpixel that a pixel is partitioned into. If S is given scale factor a pixel contains S^2 subpixels.

(4) Calculating distance between subpixel and neighboring subpixels

For calculating the attractiveness value the distance is a necessary parameter. The Euclidean distance between a pixel $P_m(Xm, Y_m)$ and subpixel $qi\ (x_i, y_i)$and a subpixel is calculated using equation 1 as shown in Figure 4

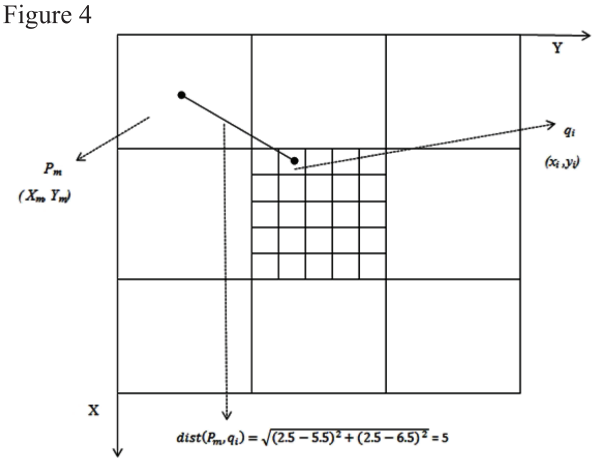

Figure 4: Distance calculation between a pixel and subpixel

$$d(P_m, q_i) = \sqrt{(X_m - x_i)^2 + (Y_m - y_i)^2} \quad (1)$$

(5) Initial non-random allocation of subpixel

The output of subpixel classification, i.e. fraction of class in a particular pixel, is represented as $fract_k^j$ where j (*j=1, 2, ...b*) represents a class and k (*k=1, 2, ...mxn*). Number of subpixels belonging to particular class is calculated. Consider a case of subpixel classification with factor 2 and a pixel has fraction of 0.75. It implies that each pixel has (2^2 =) 4 subpixels and fraction 0.75 indicates that (4 x 0.75 =) 3 subpixels belong to one class and the remaining 1 subpixel to some other class. For each subpixel within a pixel, the attractiveness to a class is evaluated as function of distance of its neighbors as shown in figure 5, which is calculated using equation 2.

				1.60	1.06
				1.06	1.12
		4.22	3.39		
		3.58	2.82		
1.67	1.72				
1.06	1.12				

(a)

				1.31	0.96
				1.57	1.08
		2.82	3.26		
		3.39	4.14		
1.12	1.41				
1.06	1.60				

Figure 5: Attractiveness values corresponding to (a) Class A; and (b) Class B

$$A_{i,j} = \sum_{k=1}^{M} fract_k^j X dist_{i,k}^{-1} \qquad (2)$$

where

$A_{i,j}$ = attractiveness of subpixel i to class j.

M = number of neighborhood pixel

$fract_k^j$ = proportion of neibhorhood pixel k per class j

$dist_{i,k}^{-1}$ = inverse distance function between subpixel i and neigborhood pixel k

Attractiveness corresponding to each class is calculated and attractiveness matrix corresponding to each class is obtained. For initial allocation the attractiveness values are sorted and class having highest attractiveness is allocated to pixel based on proportions as shown in figure 5. However, there can be some multiple and non-allocated subpixel as shown in Figure 6.

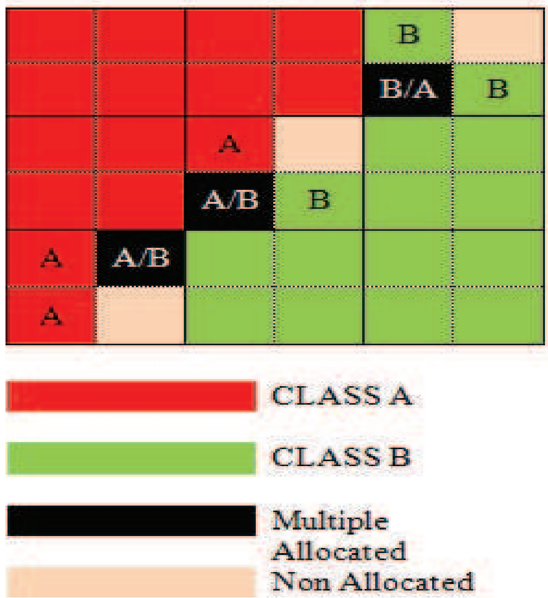

Figure 6: Initial Allocation based on attractiveness value

(6) Correcting multiple /non allocated subpixels

The problem of multiple and non-allocated subpixel is resolved as first image is scanned to find multiple and non-allocated subpixel. The value of $A_{i,j}$ for selected pixels are sorted in decreasing order. The binary variable related to maximum amount of $A_{i,j}$ showing presence or absence of class is kept as it is in multiple allocated subpixel (i.e.corresponding to maximum $A_{i,j}$). Then the next highest value of $A_{i,j}$ is selected and corresponding pixel swaps with subpixel that is not allocated to any class. The procedure continues until every sub-pixel is allocated with only single class. The obtained image is shown in figure 7.

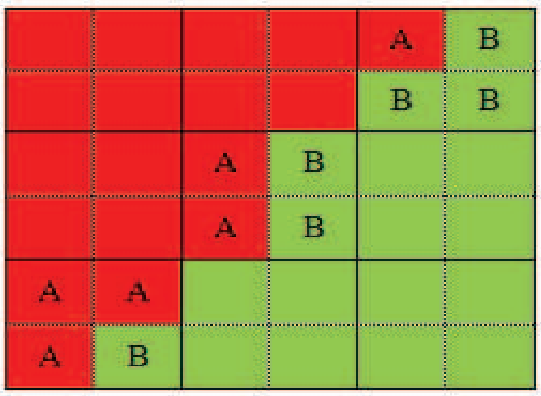

Figure 7: Subpixel mapped image

4. Results

The super resolution algorithm was programmed using Matlab7.14 version and executed on executed on an Intel core i5 processing with 4 GB Random Access Memory. The proposed method for enhancing the object boundaries was checked for performance using synthetic data and multispectral data. Initially the synthetic image was degraded then the proposed methodology was applied to enhance object boundaries. The results can be visually analyzed as shown in Figure 8. The classification accuracy for synthetic image was classified the maximum accuracy was obtained at a scale factor of S=6. The overall results are shown in Table1.

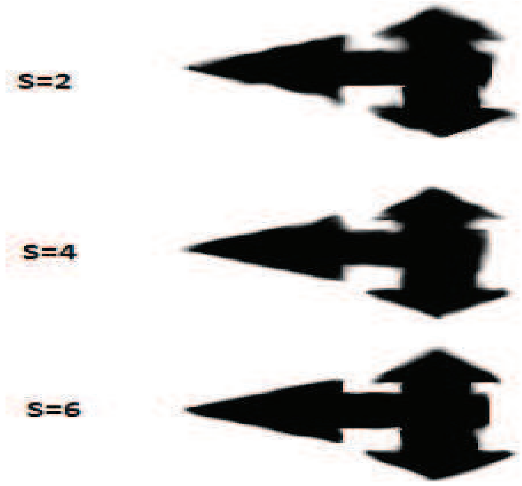

Figure 8: Results of proposed methodology on Synthetic image.

Table 1: Classification accuracy for synthetic image

Scale Factor	Classification Accuracy
2	74.8%
4	76.4%
6	78.2%

To evaluate the performance of proposed method on multispectral satellite image the Landsat 8 data was considered. The image consists of a single aircraft. The initial fractional abundances are obtained using SVM technique. The output of SVM technique is then provided as input to super resolution mapping process. The method is illustrated for scale factor S= 2, 4, 6 and 8. The results, interpreted visually, shows the best results are obtained at S=8 as shown in figure 9.

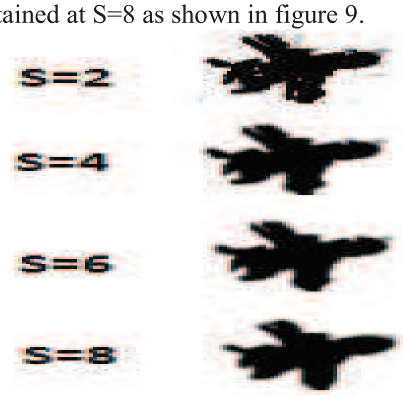

Figure 9: Results of proposed method using satellite image

The accuracy of proposed method depends on the various factors like the accuracy of subpixel classification, scale factor, window size. The method assumes that subpixel maps obtained from soft classification as accurate. However the algorithms have to be tested using output from various subpixel classifiers. Also scale factor and window size must be taken into consideration. This would be considered in future work.

5. Conclusion

The proposed algorithm provides better accuracy as compared to other techniques. In terms of visual interpretation the method also produces better accuracy.

Acknowledgment

The authors would like to thank Mr. Suresh Merugu, Research Scholar, Indian Institute of Technology Roorkee for his kind support and help.

References

Arora, M.K. and K.C. Tiwari (2013). Subpixel target enhancement in hyperspectral images, Defence Science Journal, Vol. 63, No. 1, 2013, pp. 63-68.

Atkinson. P.M (1997). Mapping subpixel boundaries from remotely sensed images."Innovations in GIS4, Z.Kemp, Ed.Bristol, P.A.: Taylor & Francis, pp.166–169.

Atkinson, P.M. (2009). Issues of uncertainty in super-resolution mapping and their implications for the design of an inter-comparison study" International journal of remote sensing.30 (20), 5293-5308.

Boucher A, and P.C. Kyriakidis (2006). Super-resolution land cover mapping with indicator geostatistics, Remote Sensing of Environment. 104, 264-282.

Kasetkasem, T., M.K. Arora and P.K. Varshney (2005). Super-resolution land cover mapping using a Markov random field based approach. Remote Sensing of Environment. 96, 302-314.

Mertens K.C, B. De Baets, L.P.C Verbeke and De Wulf (2004). A sub-pixel mapping algorithm based on sub-pixel/pixel spatial attraction models. International Journal of Remote P.M Atkinson, "Resolution manipulation and sup-pixel mapping," Remote Sensing Image Analysis: Including the Spatial Domain. Kluwer Academic, New York, 51-70.

Muada.M. and G.M. Foody (2010). Super-resolution analysis for accurate mapping of land cover and land cover pattern. In Proceeding of the IEEE International Geoscience and Remote Sensing Symposium (IGARSS), Honolulu, Hawaii, USA, 25-30.

Suresh, M. and K. Jain (2013a). Colorimetrically resolution enhancement method for satellite imagery to improve land use. 14th ESRI User Conf. id: UCP0046, New Delhi, India, 11-12th Dec, 2013.

Suresh, M. and K. Jain (2013b). To generate high resolution images (conventional subpixel) from low resolution satellite images: Colorimetry concept. ISG & ISRS, Visakhapattanam, India, 4-6th Dec, 2013.

Suresh, M. and K. Jain (2013c). To detect infrastructural damages caused by natural disaster using low resolution images. Joint International Workshop of ISPRS & INCOIS WGVIII/1&WGIV/4on Geospatial Data for Disaster and Risk Reduction, Hyderabad, India, 21-22nd Nov, 2013.

Suresh, M. and K. Jain (2013d). Subpixel analysis on hypothetical image by using colorimetry. International Journal of Recent Technology and Engineering (IJRTE), ISSN: 2277-3878, Vol. 2, Issue-4, Sep, 2013.

Suresh, M. and K. Jain (2014). A Review of Some Information Extraction Methods, Techniques and their Limitations for Hyperspectral Dataset" International Journal of Advanced Research in Computer Engineering & Technology (IJARCET), Volume 3 Issue 3, March 2014, ISSN: 2278 – 1323, pp 2394-2400.

Tatem, A.J., H.G. Lewis, P.M. Atkinson and M.S. Nixon (2001a). Super-resolution target identification from remotely sensed image using a Hopfield neural network, IEEE),Transactions on Geoscience and Remote Sensing. 39(4), 781-796.

Tatem, A.J. H.G. Lewis, P.M. Atkinson and M.S. Nixon (2001b). Multiple-class land-cover mapping at the sub-pixel scale using a Hopfield neural network. International Journal of Applied Earth Observation and Geoinformation. 3(2), 184-190

Tobler W,(1970) "A computer movie simulating urban growth in the Detroit region." Economic Geography, 46(2), pp. 234-240.

Verhoeye, J. and De Wulf (2002). Land cover mapping at sub-pixel scales using linear optimization techniques. Remote Sensing of Environment, 79(1), 96-10.