esri India
15th Esri India User Conference 2014
Geo-Enabling Digital India
2014

SUBPIXEL LEVEL CLASSIFICATION USING COLORIMETRIC COLOR SPACE

Suresh Merugu[1], Dr Kamal Jain[2]
[1] Research Scholar, Indian Institute of Technology Roorkee, Haridwar, Uttarakhand, India, sureshmerugu.iitr@gmail.com.
[2] Professor, Indian Institute of Technology Roorkee, Haridwar, Uttarakhand, India

Abstract:

High resolution imaging has paved the way to uncover targets which used to remain uncovered while analyzing data from multispectral sensors. In most cases, however, the spatial resolution for many satellite based sensors is still too coarse in comparison to their spectral resolution. Thus, a target of interest may get spectrally resolved but may not spatially due to small size. Such a target may partly occupy one pixel or several pixels and may manifest itself in several ways. The problem is referred to as subpixel target detection and enhancement. In subpixel classification, the aim is to recover the target, which due to its smaller size than the spatial resolution is completely embedded in the pixel.

In this paper, a new CIELAB euclidean distance based super-resolution mapping method has been presented. In this method, the subpixel target detection and enhancement is performed by adjusting spatial distribution of abundance fraction within a pixel of a high resolution image with tristimulus variations and color differences in colorimetry. A colorimetric color space clustering algorithm is proposed and utilized to do clustering on the colorimetric color feature space of pixels. Results obtained at different resolutions indicate that super-resolution mapping may effectively be utilized in enhancing the anomalies detection at sub-pixel level.

Key Words: CIE color space, colorimetry, super resolution mapping, color clustering technique, subpixel classification, anomalies/target detection.

About the Author:

Mr. Suresh Merugu

Name: **Suresh Merugu**

Date of Birth: 16/08/1979

Designation: Ph. D, QIP Research Scholar

Organization: Indian Institute of Technology Roorkee and Assistant Professor, Department of ECE, CMRCET, Hyd.

Specialization: Digital Image Processing, Remote Sensing and GIS

E mail ID: sureshmerugu.iitr@gmail.com

Contact No: +91 – 8126906333 & 9848276627

1. Introduction

One of most important technique in remote sensing is image classification which is widely used to extract land cover information and have an important use in environment monitoring and mineral exploration. Accurate and reliable information of land cover has a particular importance for environment planning and management issues. So it is necessary to reduce the uncertainty in different steps of remote sensing process to improve accuracy of information derived. Remote sensing image contains a mix of pure and mixed pixels. Pure pixel contains only one feature such as vegetation or urban area while mixed pixel defined as pixel containing more than one feature. Mixed pixel occurs when the spatial frequency is higher than the interval between pixels. Mixed pixel affects the accuracy of classification process. Without overcoming the problem of mixed pixel, the full potential of remote sensing in extracting land use land cover information will remain unrealized (Foody, 2006).

The remote sensing data imaging has paved the way to uncover details of material which used to remain uncovered while acquiring data from multi/hyperspectral sensors. In most cases, however, the spatial resolution for many satellite based multi/hyperspectral sensors is still too coarse in comparison to their spectral resolution. Thus, an area of interest may get spectrally resolved but may not spatially due to its small size. Such a target may partly occupy one pixel or several pixels and may manifest itself in several ways which can be called as anomaly, as can be seen from Figure-1. For example, a target may lie completely within a pixel or it may cover one pixel fully and also simultaneously exist partially in all the eight pixels in the neighborhood with respect to its scale factor, here in this example the scale factor is three. In both the cases, the problem is referred to as subpixel target detection. In subpixel level target detection, the ultimate aim is to recover the target or anomaly, which due to its smaller size than the spatial resolution is completely embedded in the pixel. Except when it fills single pixel completely, the pixel containing the target may also contain several other component materials.

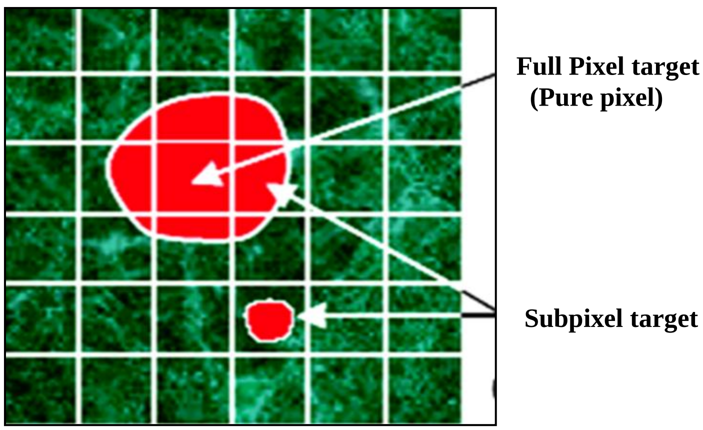


Figure 1.1: Showing the full pixel and subpixel target

2. Literature Review

(Ling et al. 2010) proposed a method for land cover mapping using super resolution technique for prediction of spatial distribution of each land cover class at the sub-pixel scale. All the low resolution remote sensing images are classified with soft classification method to get fraction images and using these all fractional images as an input to the Hopfield Neural network of super resolution mapping for extraction of high resolution land cover map. From the experiments it was observed that, high overall accuracy and better kappa coefficients are achieved with low scale factor and more fractional images.

(Niroumand et al. 2012) mixed pixels could be considered as a major source of uncertainty through classification process of satellite imagery. In this regard, the use of soft classifiers is often inevitable in order to increase the accuracy of land cover estimates. Although soft classifiers provide detailed information for each pixel, spatial arrangement of sub-pixels remains unknown. Super Resolution Mapping (SRM) has opened up a new horizon to produce finer spatial resolution maps using the outputs of soft classifiers. In this way, spatial optimisation techniques are the most applicable ones. However, random allocation of sub-pixels and iterative procedure of optimisation are the main limitations of current methods (e.g. Hopfield

Neural Network, Simulated Annealing). This paper attempts to provide an optimisation approach based on the pixel swapping technique in order to simplify the concept and to reduce the iteration procedure and is time effective.

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 us 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 M and Jain K, 2013&14). 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 M and Jain K, 2013&14).

3. Experimental Data

An archived multispectral image from QuickBird imagery sensor acquired over Rome City which is having roof tops and roads, has been used(Figure 5.1). The image is available as example data in ENVI image processing software. After removal of water absorption and bad bands, image already available as reflectance spectra have been considered. The image contains building roofs, roads, vegetation, and water body (Figure 5.2) centered at pixel coordinates (row, column), (244, 145), (232,137), (199,158), (89, 11), (70, 22). From this data, an image of size 40 x 40 pixels has been extracted containing roads and buildings. It may be noticed that these two targets fall under shadow and may be treated as difficult targets to detect. For the set of experiments in this study, regions containing both full and partially full pixels have been extracted. The data was corrected for atmospheric effects and available in the website but the exact atmospheric condition and the atmospheric correction algorithm are not available in the website and we assume that the reflectance dataset is good but not perfect.

4. Methodology

4.1. Sub pixel target detection using local spatial information

Enhancing sub pixel level target detection involved changing the global mean value with the local mean value. Using the local mean value is definitely double edged: on one hand, every one would expect that the closer the points used to evaluate the background are to the suspected target, the more likely it is that the estimate will be accurate. On the other hand, the noise in the estimate will decrease given more points entering into the estimation, assuming that the background is stationary and the noise is linearly added to the background and independent thereof. The main empirical experience confirmed by several studies is that the closer one chooses the pixels the better, with this condition that no one should have target contamination of the background pixels.

One should note that no one can deal here with a “local” covariance matrix which would change when evaluating each pixel in the image. Rather, one should use the same covariance matrix throughout the image; it will simply be based on the difference of the sample pixels and their “local” background.

Since while dealing with a subpixel target, which in the physical domain can affect only pixels in a limited spatial area surrounding the center of the target, in this paper nearest neighbors approach is used to estimate the value of the test pixels.
In the literature, it is observed that different transforms are used to extract desired information from remote-sensing images. Segmentation evaluation techniques can be generally divided into two categories (supervised and unsupervised). The first category is not applicable to remote sensing because an optimum segmentation (ground truth segmentation) is difficult to obtain. Moreover, available segmentation evaluation techniques have not been thoroughly tested for remotely sensed data. Therefore, for comparison purposes, it is possible to proceed with the classification process and then indirectly assess the segmentation process through the produced classification accuracies. Clustering is a mathematical tool that attempts to

discover structures or certain patterns in a data set, where the objects inside each cluster show a certain degree of similarity. For image segment based classification, the images that need to be classified are segmented into many homogeneous areas with similar spectrum information firstly, and the image segments‟ features are extracted based on the specific requirements of ground features classification.

The colour homogeneity is based on the standard deviation of the spectral colours, while the shape homogeneity is based on the compactness and smoothness of shape. There are two principles in the iteration of parameters: 1) In addition to necessary fineness, we should choose a scale value as large as possible to distinguish different regions; 2) we should use the colour criterion where possible. Because the spectral information is the most important in imagery data, the quality of segmentation would be reduced in high weightiness of shape criterion. This work presents a novel image segmentation based on colour features from the images. In this we did not used any training data and the work is divided into two stages. First enhancing color separation of satellite image using decor relation stretching is carried out and then the regions are grouped into a set of five classes using K-means clustering algorithm. Using this two-step process, it is possible to reduce the computational cost avoiding feature calculation for every pixel in the image. Although the colour is not frequently used for image segmentation, it gives a high discriminative power of regions present in the image. Colour segmentation is an essential issue with regard to vision applications, such as object detection and navigation. The process of color segmentation consists of color representation, color feature extraction, similarity measurement and classification.

4.2. Colorimetric color space

Step 1: Acquire Image

Read in the residential.tif image, which is an image of Rome city. One can acquire an image using the following functions in the Image Acquisition Toolbox.

Step 2: Convert Image from RGB Color Space to colorimetric L*a*b* Color Space

How many colors does one can see in the image if do ignore variations in brightness? There are building roofs, roads, vegetation and water body. Notice how easily one can visually distinguish these class colors from one another. The colorimetric L*a*b* color space (also known as CIELAB or CIE L*a*b*) enables you to quantify these visual differences. The L*a*b* color space is derived from the CIE XYZ tristimulus values. The L*a*b* space consists of a luminosity layer 'L*', chromaticity-layer 'a*' indicating where color falls along the red-green axis, and chromaticity-layer 'b*' indicating where the color falls along the blue-yellow axis. All of the color information is in the 'a*' and 'b*' layers. You can measure the difference between two colors using the Euclidean distance metric.

Step 3: Calculate Sample Colors in colorimetric L*a*b* Color Space for Each Region

You can see six major class colors in the image: the background color and other class colors. Notice how easily you can visually distinguish these colors from one another. The L*a*b* colorspace (also known as CIELAB or CIE L*a*b*) enables to quantify these visual differences. The L*a*b* color space is derived from the CIE XYZ tristimulus values. The L*a*b* space consists of a luminosity 'L*' or brightness layer, chromaticity layer 'a*' indicating where color falls along the red-green axis, and chromaticity layer 'b*' indicating where the color falls along the blue-yellow axis. Your approach is to choose a small sample region for each color and to calculate each sample region's average color in 'a*b*' space. You will use these color markers to classify each pixel. To simplify this, load the region coordinates that are stored in a MAT-file.

Step 4: Classify Each Pixel Using the Nearest Neighbor Rule

Each color marker now has an 'a*' and a 'b*' value. One can classify each pixel in the given image by calculating the Euclidean distance between that pixel and each color marker. The smallest distance will tell you that the pixel most closely matches that color marker. For example, if the distance between a pixel and the red color marker is the smallest, then the pixel would be labelled as a red pixel. Create an array that contains your color labels, i.e., 0 = background, 1 = red, 2 = green, 3 = purple, 4 = magenta, and 5 = yellow.

Step 5: Display Results of Nearest Neighbor Classification

The label matrix contains a color label for each pixel in the given image. Use the label matrix to separate objects in the original image by color.

Step 6: Display 'a*' and 'b*' Values of the Labelled Colors.

One can see how well the nearest neighbor classification separated the different color populations by plotting the 'a*' and 'b*' values of pixels that were classified into separate colors. For display purposes, label each point with its color label.

5. Results and Discussion

The proposed algorithm implemented and tested its performance on a number of satellite images with the help of Matlab. In order to further evaluate the performance of the proposed technique, QuickBird imagery has been considered. The dataset consists of buildings and roads as targets. Supervised classification problem where each and every pixel is classified into different groups using maximum likelihood method in ArcGIS10 software. The effective features are extracted based on pixel level and a label is assigned to every pixel through which regions are formed, but the classification accuracy is not that much accurate because the main problem is mixed pixel. Thereafter, the proposed colorimetric color space technique has been applied to perform super resolution. However, due to non-availability of reference data, the super resolved images have been evaluated visually and not quantitatively. The proposed colorimetric Euclidean distance technique produces satisfactory results across all factors. The reason for success of this method lies in the fact that it does not involve any iterative convergence and is based on the stored rankings of attractiveness values of the super resolved mixed pixels.

Figure 5.1: Input QuickBird imagery

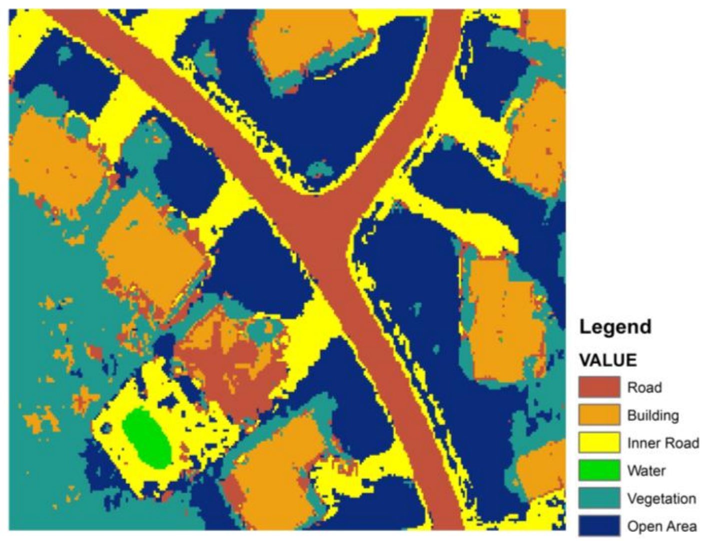
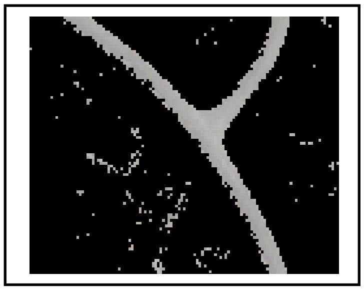
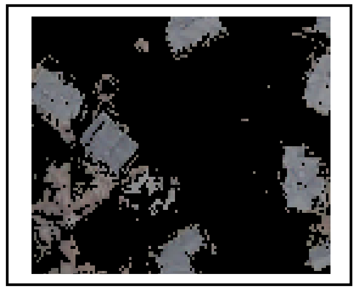
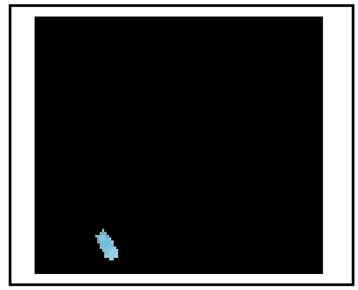
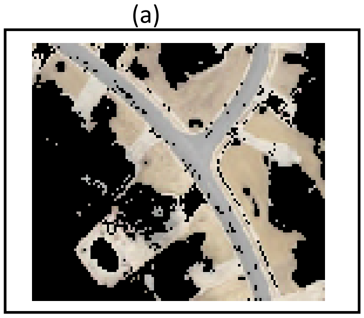
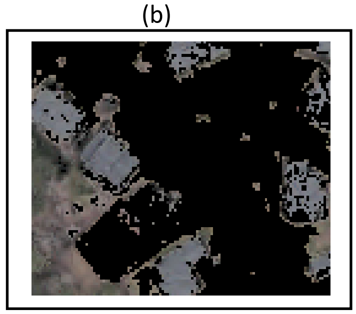


Figure 5.2: Showing the different classes classified using maximum likelihood method in ArcGIS10

(a) (b) (c)

(d) (e) (f)

Figure 5.3: (a) Showing the fraction abundance of road information using the proposed technique (b) building information (c) water information (d) open area information (e) vegetation information (f) inner roads information.

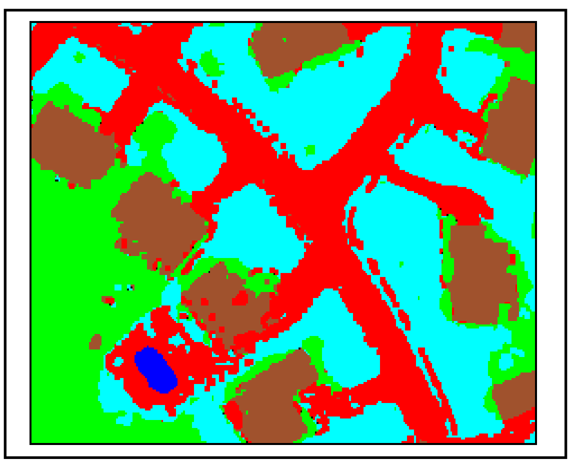


Figure 5.4: Showing the different classes classified using the proposed colorimetric color space

6. Conclusions

This paper proposed, implemented and tested using colorimetric classical model for image classification for information extraction at subpixel level. The designed models were implemented to segment the image and their results were compared. From the experimental results, it is inferred that Adaboost correctly predicts most of the data samples, reduces error and increases accuracy when compared to classification method in ArcGIS. The technique achieves subpixel level information extraction in multispectral images by adjusting spatial distribution of abundance fraction within a pixel. The experiments have been conducted using sample imagery of QuickBird dataset. The performance of the proposed technique measured in terms of classification accuracy and CPU time for both the datasets have been found satisfactory and encouraging. The major advantage of the proposed technique has been the near constant CPU processing time despite increase in scale factor or in complexity. Though the technique produces good results, one of the limitations of the proposed technique lies in the use of a linear

Euclidean distance as a measure of attractiveness. Future studies may consider the use of a non-linear measure for ranking subpixels for spatial distribution, particularly in case of multi-class problems.

7. References

1. **D. E. Ilea and P. F. Whelan**. Image segmentation based on the integration of color-texture descriptors—a review. Journal of Pattern Recognition, 44(10-11):2479–2501, October–November 2011.
2. **Foody, G.M., 2006,** approaches for the production and evaluation of fuzzy land cover classification from remotely-sensed data. International Journal of Remote Sensing, 17, pp. 1317-1340.
3. **J. Ninga, L. Zhanga, D. Zhanga, and C. Wu**. Interactive image segmentation by maximal similarity based region merging. Journal of Pattern Recognition, 43(2):445–456, February 2010.
4. **J. Ninga, L. Zhanga, D. Zhanga, and C. Wu.** Multivariate image segmentation using semantic region growing with adaptive edge penalty. Journal of Pattern Recognition, 19(8):2157–2170, August 2010.
5. **Ling, F. & Fu, B., 2009**, Super-resolution mapping of urban buildings with remotely sensed imagery based on prior shape information, *IEEE Conference on Urban Remote Sensing Joint Event.*
6. **Ling, F., Du, Y., Xiao, F., Xue, H. & Wu, S., 2010**, Super resolution land cover mapping using multiple sub-pixel shifted remotely sensed images, International Journal of Remote Sensing, 31(19), pp. 5023-40.
7. **M. Niroumand J, A. R. Safdarinezhad, M. R. Sahebi, M. Mokhtarzade, 2012,** a Novel Approach to Super Resolution Mapping of Multispectral Imagery Based on Pixel Swapping Technique, (ISPRS Annals of the Photogrammetry, Remote Sensing and Spatial Information Sciences, Volume I-7, XXII ISPRS Congress, September 2012).
8. **Merugu Suresh, Kamal Jain, 2014,** "A New Super Resolution Mapping Algorithm by Combining Pixel and Subpixel-Level Spatial Dependences with Colorimetry" Journal of Indian Society of Remote Sensing (ISRS), 10/2014; 42(4):10, Springer.
9. **Merugu Suresh, Kamal 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.
10. **Suresh Merugu, Kamal Jain, 2013**, colorimetrically resolution enhancement method for satellite imagery to improve land use 14th ESRI User Conf. id: UCP0046, New Delhi, India, 11-12th Dec, 2013.
11. **Suresh Merugu, Kamal Jain, 2013**, sub pixel analysis on hypothetical image by using colorimetry International Journal of Recent Technology and Engineering (IJRTE), ISSN: 2277-3878, Vol. 2, Issue-4, Sep, 2013.
12. **Suresh Merugu, Kamal Jain, 2013**, 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.
13. **Suresh Merugu, Kamal Jain, 2013**, to generate high resolution images (conventional subpixel) from low resolution satellite images: colorimetry concept" ISG & ISRS, Visakha, India, 4-6th Dec, 2013.
14. **Tatem, A.J., Lewis, H.G., Atkinson, P.M. and Nixon, M.S., 2002.** "Super-resolution land cover pattern prediction using a Hopfield neural network." Remote Sensing of Environment 79: 1-14.
15. **Verhoeye, J., and De Wulf, R., 2002.** "Land cover mapping at sub-pixel scales using linear optimization techniques." Remote Sensing of Environment 79: 96-104.
16. **Wang, L., and Wang, Q., 2013.** "Subpixel mapping using markov random field with multiple spectral constraints from subpixel shifted remote sensing images."IEEE Geoscience and Remote Sensing Letters 10: 598-602.
17. **Wang, L., Zhang, Y., and Li, J., 2006. "**BP neural network based SubPixel mapping method." Intelligent Computing in Signal Processing and Pattern Recognition 345: 755-760.
18. **Wang, Q., Wang, L., and Liu, D., 2012a.** "Integration of spatial attractions between and within pixels for sub-pixel mapping." Journal of Systems Engineering and Electronics 23: 293-303.
19. **Wang, Q., Wang, L., and Liu, D., 2012b.** "Particle swarm optimization-based sub-pixel mapping for remote-sensing imagery." International Journal of Remote Sensing 33: 6480-6496.
20. **Zhong, Y. and Zhang, L., 2013.** "Sub-pixel mapping based on artificial immune systems for remote sensing imagery." Pattern Recognition 46: 2902-2926.