IJETST- Vol.||04||Issue||08||Pages 5725-5733||August||ISSN 2348-9480 2017

Open access Journal International Journal of Emerging Trends in Science and Technology
IC Value: 76.89 (Index Copernicus) Impact Factor: 4.219 DOI: https://dx.doi.org/10.18535/ijetst/v4i8.46

Design and Development of Hyper Spectral Image Classification Using Enhanced Mean Shift Segmentation in Image Mining

Authors
Dr. S.Thavamani
M.Sc., M.Phil., Ph.D.,
Associate Professor, Department of Computer Applications,
Sri Ramakrishna College of Arts and Science (autonomous)
(Formerly S.N.R SONS College)
Coimbatore –641006, Tamil Nadu, India.

Abstract
Hyper spectral imaging is becoming an important analytical tool for generating land-use map. High dimensionality in hyper spectral remote sensing data can guaranty in principle a detailed discrimination of the observed surfaces overcoming the intrinsic limitation of lower spectral resolution data. We propose an ovel approach for solving the perceptual grouping problem in vision. In the existing methods the image segmentation was done by using special spectral classification. Special spectral may have some of the problems such as quality and clarity of the particular image. We show that an efficient computational technique based on a generalized region value problem can be used to optimize this criterion. In our proposed method Enhanced mean shift algorithm is used for segmenting the part of the particular image. Experimental result use accuracy and execution time parameters to show the performance. It takes low computational complexity and also accurate result for real-time image segmentation processing

Keywords- Hyper spectral Imaging (HIS), Image Classification, Enhanced Mean Shift Clustering (EMSC) algorithm, Spatial Spectral Segmentation

1. Introduction

Data mining can be viewed as a result of the natural evolution of information technology. An evolutionary path has been witnessed in the database industry in the development of the following functionalities: data collection and database creation, data management (including data storage and retrieval, and database transaction processing), and data analysis and understanding (involving data warehousing and data mining).

Image mining concerns the extraction of implicit knowledge, image data relationship, or other patterns not explicitly stored in the images. It is more than just an extension of data mining to image domain. Image mining is an interdisciplinary endeavour which draws upon expertise in computer vision, image understanding, data mining, machine learning, database, and artificial intelligence.

Image mining concerns the extraction of implicit knowledge, image data relationship, or other patterns not explicitly stored in the images. It is more than just an extension of data mining to image domain. Image mining is an interdisciplinary endeavour which draws upon expertise in computer vision, image understanding, data mining, machine learning, database, and artificial intelligence.

While multispectral images have been in regular use since the 1970s, the widespread use of hyper spectral images is a relatively recent trend. Hyper spectral imaging, also known as imaging spectrometry, is now a reasonably familiar concept in the world of remote sensing. However, for many remote sensing specialists who have not yet had the opportunity to use hyper spectral imagery in their work, the benefits of hyper spectral imagery may still be vague.

Literature Survey

Hyper spectral image classification has attracted extensive research efforts in the recent decade. The main difficulty lies in the few labelled samples versus the high dimensional features. To this end, it is a fundamental step to explore the relationship among different pixels in hyper spectral image classification, toward jointly handing both the lack of label and high dimensionality problems. In the hyper spectral images, the classification task can be benefited from the spatial layout information. In this work, the author has proposed a hyper spectral image classification method to address both the pixel spectral and spatial constraints [1], in which the relationship among pixels is formulated in a hyper graph structure.

In this work, a new method for improving the classification performance of hyper spectral images with the aid of derivative information is investigated in [2]. Gray scale image have been discussed in many algorithm [5]. There are huge varieties of image segmentation technique; 50% considered general purpose and 50% designed for specific classes of images [6]. In [7] the author gives an overview of the utilization of segmentation method in remote sensing.

Hyper spectral imaging techniques have been widely used for a variety of applications pertaining to vegetation species identification. With its rich spectral information, HSI is a powerful tool to detect and characterize vegetation species and their health. To avoid this over-dimensionality problem, feature selection or feature extraction must be performed to reduce the dimensionality of HSI data. This problem is further exacerbated when spatial information is also exploited in conjunction with spectral information. In [3] and [8] proposed a feature selection approach for extracting the most meaningful spatial and spectral features for a vegetative stress detection problem - genetic algorithms based linear discriminate analysis (GA-LDA).

In [4] Bezdek has reviewed, with somewhat variable coverage, the nine MR image segmentation techniques. A wide array of approaches has been discussed; each has its merits and drawbacks. We have also given pointers to other approaches not discussed in depth in this review.

A graph-based model has naturally encapsulates both the spatial and spectral information. Once the graph has been constructed, we then use spectral graph-based approaches (based on Laplacian eigenmaps and normalized cuts) to perform dimensionality reduction and segmentation. Moreover, the naturally sparse structure of the graph allows us to use specialized, sparse linear algebra routines for the Eigen-analysis, allowing us to apply the model on realistic sized imagery.

2.1 Problem Specification

- Fast computers, sensitive detectors, and large data storage capacities are needed for analysing hyper spectral data.
- Significant data storage capacity is necessary since hyper spectral cubes are large, multidimensional datasets, potentially exceeding hundreds of megabytes.
- All of these factors greatly increase the cost of acquiring and processing hyper spectral data.
- It is very difficult to get accurate result in this spatial spectral graph method and also it takes more time for computation task.

3.Working Methodology

3.1 Enhanced Mean Shift Clustering

The enhanced mean shift algorithm is a nonparametric clustering technique which does not require prior knowledge of the number of clusters, and does not constrain the shape of the clusters. This proposed method is used to overcome from the problem which is mentioned above.

Given n data points xi, i = 1, ..., n on a d-dimensional space Rd, the multivariate kernel density estimate obtained with kernel K(x) and window radius h is

$$f(x) = \frac{1}{nh^d}\sum_{i=1}^{n} K\left(\frac{x - x_i}{h}\right)$$

For radially symmetric kernels, it suffices to define the profile of the kernel k(x) satisfying

$$K(X) = c_{k,d}k(\|X\|^2)$$

where ck,d is a normalization constant which assures K(x) integrates to 1. The modes of the density function are located at the zeros of the gradient function rf(x) = 0.

The gradient of the density estimator (1) is

$$\nabla f(x) = \frac{2c_{k,d}}{nh^{d+2}} \sum_{i=1}^{n} (x_i - x) g\left(\left\|\frac{x - x_i}{h}\right\|^2\right)$$

$$= \frac{2c_{k,d}}{nh^{d+2}} \left[\sum_{i=1}^{n} g\left(\left\|\frac{x - x_i}{h}\right\|^2\right)\right] \left[\frac{\sum_{i=1}^{n} x_i g\left(\left\|\frac{x - x_i}{h}\right\|^2\right)}{\sum_{i=1}^{n} g\left(\left\|\frac{x - x_i}{h}\right\|^2\right)}\right] - x$$

where g(s) = −k0(s). The first term is proportional to the density estimate at x computed with

kernel G(x) = cg,dg(kxk2) and the second term

$$m_h(X) = \frac{\sum_{i=1}^{n} X_i g\left(\left\|\frac{X - X_i}{h}\right\|^2\right)}{\sum_{i=1}^{n} g\left(\left\|\frac{X - X_i}{h}\right\|^2\right)} - X$$

is the enhanced mean shift. The enhanced mean shift vector always points toward the direction of the maximum increase in the density. The enhanced mean shift procedure, obtained by successive

• Computation of the enhanced mean shift vector $m_h(X)$,

• Translation of the window $X_i + 1 = X_i + m_h(X)$

is guaranteed to converge to a point where the gradient of density function is zero.

3.2 PHASE–I: Filtering

The filtering step of the enhanced mean shift segmentation algorithm consists of analysing the probability density function underlying the image data in feature space. Consider the feature space consisting of the original image data represented as the (x, y) location of each pixel, plus its colour in L*u*v* space (L_, u_, v_). In terms of segmentation, it is intuitive that the data points close to these high density points (modes) should be clustered together. Note that these modes are also far less sensitive to outliers than the means of, say, a mixture of Gaussians would be.

The enhanced mean shift filtering step consists of finding the modes of the underlying pdf and associating with them any points in their basin of attraction. Unlike earlier techniques, the enhanced mean shift is a non-parametric technique and hence we need to estimate the gradient of the pdf, f(x), in an iterative manner using kernel density estimation to find the modes. For a data point x in feature space, the density gradient is estimated as being proportional to the enhanced mean shift vector:

$$\widehat{\nabla} f(\mathrm{x}) \propto \frac{\sum_{i=1}^{n} \mathrm{x}_i g\left(\left\|\frac{\mathrm{x}-\mathrm{x}_i}{h}\right\|\right)}{\sum_{i=1}^{n} g\left(\left\|\frac{\mathrm{x}-\mathrm{x}_i}{h}\right\|\right)} - \mathrm{X}$$

where xi are the data points, x is a point in the feature space, n is the number of data points (pixels in the image), and g is the profile of the symmetric kernel G. We use the simple case where G is the uniform kernel with radius vector h. Thus the above equation simplifies to:

$$\widehat{\nabla} f(X) \propto \left[\frac{1}{|S_x h_s h_r|} \sum_{x_i \in S_x h_s h_r} X_i\right] - X$$

Where $S_x h_s h_r$ represents the sphere in feature space centered at x and having spatial radius h_s and colour (range) radius h_r , and the X_i represent the data points within that sphere. For every data point (pixel in the original image) x we can iteratively compute the gradient estimate in above equation and move x in that direction, until the gradient is below a threshold. Thus we have found the points where crf(x0) = 0, the modes of the density estimate. We can then replace the point x with x0, the mode with which it is associated. Finding the mode associated with each data point helps to smooth the image while preserving discontinuities. Intuitively, if two points $X_\mathbf{i}$ and $X_\mathbf{j}$ are far from each other in feature space, then xi 62 $S_x h_s h_r$ and hence Xj doesn't contribute to the enhanced mean shift vector gradient estimate and the trajectory of Xi move it away fromX_i. Hence, a pixel on either side of a strong discontinuity does not attract each other. However, filtering alone does not provide segmentation as the modes found are noisy. These noise items came from two sources. First, the mode estimation is an iterative process; hence it only converges to within the threshold provided (and with some numerical error). Second, consider an area in feature space larger than $S_x h_s h_r$ and where the colour features are uniform or have a gradient of 1. Since the pixel coordinates are uniform by design, the enhanced mean shift vector is to be 0 in this region, and the data points are not move and hence not converge to a single mode. Intuitively, however, we would like all of these data points to belong to the same cluster in the final segmentation. For these reasons, enhanced mean shift filtering is only a pre-processing step, and a second step is required in the segmentation process: clustering of the filtered data points {x0}.

The goal of image segmentation is to cluster pixels into salient image regions, i.e., regions corresponding to individual surfaces, objects, or natural part of objects.

3.2.1. Algorithm Steps for Filtering

Step 1: Upload the image for segmentation.
Step 2: Analyse the probability density function underlying the image data in feature space.
Step 3: Find the feature space of the original image by represent x and y location of each pixel, plus its colour in L*u*v* space.
Step 4: Then, input image can be segmented into a number of parts for the performance of image segmentation.
Step 5: Filtering is only a pre-processing step, and second step is required in the segmentation process of clustering of the filtered data points.

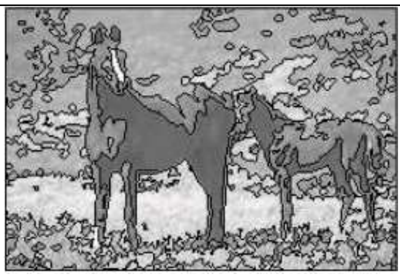
 Figure: 1 (a) Input image of horses	 Figure**:** 1 (b) Input image of tiger
 Figure: 1 (c) Segmented the input image of horses	 Figure: 1 (d) Segmented the input image of tiger

Figure 1: a) Input image of horse b) Segmented image for given input of horse c) Input image of tiger d) segmented image of given input of tiger.

The figure.1 show the performance of segmentation in enhanced mean shift technique. The segmentation can be done in a proper way then first two images are input image next two images are segmented image of the given input.

3.2.2. PHASE–II Clustering

After enhanced mean shift filtering, each data point in the feature space has been replaced by its corresponding mode. As described above, some points may have collapsed to the same mode, but many have not despite the fact that they may be less than one kernel radius apart. In the original enhanced mean shift segmentation, clustering is described as a simple post- processing step in which any modes that are less than one kernel radius apart are grouped together and their basins of attraction are merged. This suggests using single linkage clustering, which effectively converts the filtered points into segmentation.

The only other work using enhanced mean shift segmentation that speaks directly to the clustering. In this approach, a Region Adjacency Graph (RAG) is created to hierarchically cluster the modes. Also, edge information from an edge detector is combined with the colour information to better guide the clustering. This is the method used in the publicly available EDISON system, also described. The EDISON system is the implementation we use here as our enhanced mean shift segmentation system.

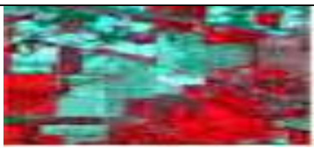
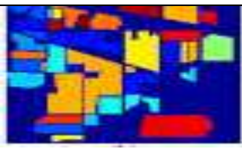
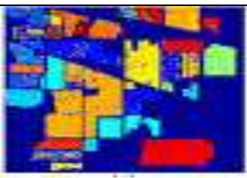
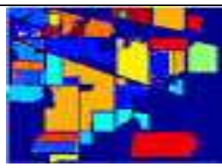
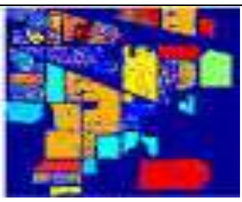
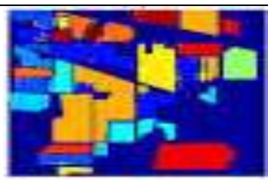
 Figure: 2 (a) Input Image	 Figure: 2 (b) Initial Step
 Figure: 2 (c) Finding Similar colors	 Figure: 2 (d) Edges are tuning
 Figure: 2 (e) Noises are removing	 Figure: 2 (f) Finally clustering similar colours

Figure 2 (a) to 2(f) shows the each and every step of clustering for a particular image.

Figure 2 (a) to 2 (f) images show the task of clustering. First image is the input image from that image it may perform the task of clustering by grouping the similar colours into one unit. T(f) similar colours are shows in one colour. After segmentation, clustering will take place to done the work.

3.2.3 Expremental Results

MATLAB is a high-performance language for technical computing. It integrates computation, visualization, and programming in an easy-to-use environment where problems and solutions are expressed in familiar mathematical notation.
Typical uses include:

- Math and computation
- Algorithm development
- Modelling, simulation, and prototyping
- Data analysis, exploration, and visualization
- Scientific and engineering graphics
- Application development, including Graphical User Interface building

MATLAB is an interactive system whose basic data element is an array that does not require dimensioning. This allows you to solve many technical computing problems, especially those with matrix and vector formulations, in a fraction of the time it would take to write a program in a scalar non-interactive language such as C or FORTRAN

Figure: 3 a) Input Image

Figure: 3 b) Spatial Spectral Classification

Figure: 3 c) Enhanced mean shift Segmentation

Figure 3 (a) Input Image, (b) Spatial Spectral Classification (c) Enhanced mean shift Segmentation for grassland image our proposed method gives accurate result when compared with other methods.

This image represent a forest image which may contains several colours such as light green, dark green, soil colour it can perform the task of segmentation and clustering. The similar colours are cluster into a single unit.

This image is used to done the work for the parameter of number of entities. That is, the above image may perform the task by reducing the amount of entities from an input image.

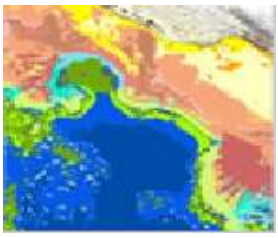


Figure: 4 a) Input Image

Figure: 4 b) Spatial Spectral Classification

Figure: 4 c) Enhanced mean shift Segmentation

Figure 4 (a) Input Image, (b) Spatial Spectral Classification (c) Enhanced mean shift Segmentation for ocean image our

Proposed method gives accurate result when compared with other methods.

This image represent a river image which may contains several colours, blue represents the water, green represents trees and remaining colour shows the sand and soil then it can perform the task of segmentation and clustering. The similar colours are cluster into a single unit and get the accurate result by using Mean Sift Segmentation method. This image is used for the parameter of accuracy. The given input image of ocean image done a good job and gives the accurate result.

Figure 5 a) Input Image

Figure 5 b) Spatial Spectral Classification

Figure 5 c) Enhanced mean shift Segmentation

Figure 5 (a) Input Image, (b) Spatial Spectral Classification (c) Enhanced mean shift Segmentation for one of the area in map image our proposed method gives accurate result when compared with other methods.

Figure 5 shows a particular location from map. Here we can perform the task segmentation and clustering by using different algorithms. But the proposed methods of enhanced mean shift segmentation give the accurate result than spatial spectral graph. This image may contains number of colours, similar colours can be clustered properly and display the output.

This image is used for parameter of execution time. This image takes less time for execution because the entities in an image are less.

Figure 6 a) Input Image

Figure 6 b) Spatial Spectral Classification

Figure 6 c) Enhanced mean shift Segmentation

Figure 6 (a) Input Image, (b) Spatial Spectral Classification (c) Enhanced mean shift Segmentation for Google map image our proposed method gives accurate result when compared with other methods.

The above image is Google map which shows large city it contains several houses displayed in small size. Here, the input image can perform the task of segmentation and clustering by using enhanced mean shift segmentation in a good manner.

This work proposed a simpler method for boundaries matching among source segmentation S_1 and target segmentation S_2. Using this matching

Strategy, we define accuracy and execution time to be proportional to the total number of unmatched pixel among two segmentations S_1 and S_2. Unmatched pixels are

particular distance. Precision (Accuracy) and recall (Execution Time) measures are defined as follows:

$$Precision(S_1, S_2) = \frac{Matched(S_1, S_2)}{|S_1|}$$

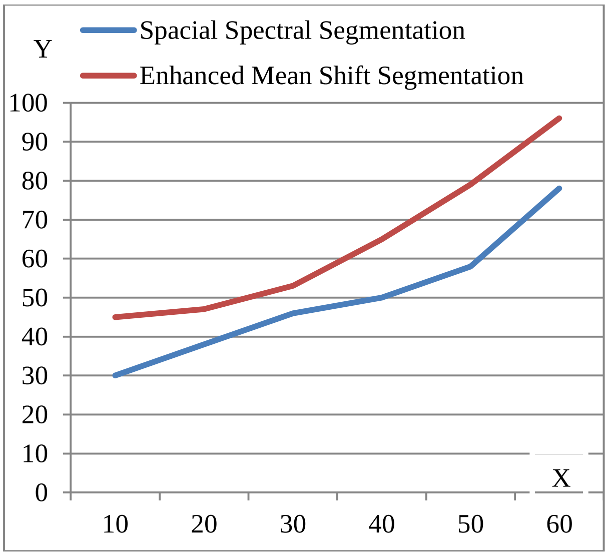
Where $Matched(S_1, S_2)$ is the number of boundary pixels in S_1 for which a suitable match is found in S_2 and $|S_1|$ is the total number of boundary pixels in S

$$Recall(S_2, S_1) = \frac{Matched(S_2, S_1)}{|S_2|}$$

3.2.4 Table 1: Accuracy and Execution time

Methods	Accuracy (%)	Execution Time (Sec)
Spatial Spectral Classification	67%	79
Enhanced mean shift Segmentation	89%	51

Table 1: Shows the Accuracy and Execution Time of existing and proposed methods



those for which a suitable match cannot be found within a particular distance. Precision (Accuracy) and recall (Execution Time) measures are defined as follows:

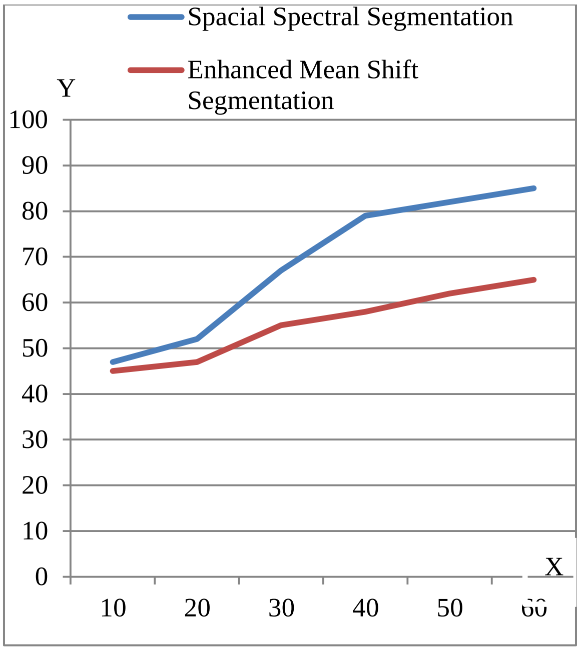


Figure 7: Accuracy and Execution Time for Proposed Method which is shown in both bar chart and line chart

The figure 7 shows that the proposed method has higher accuracy and lower execution time when compare with the existing methods.

The above figure and chart shows the performance of the existing and proposed method. From the experiment we find out that the proposed method of Enhanced mean shift Segmentation give the accurate result then Spatial Spectral Segmentation and also propose method of Enhanced mean shift Segmentation performs the task with less computation time.

4. Conclusions

In this paper a novel image segmentation algorithm has been proposed and designed based on the mean shift algorithm. The effectiveness and robustness of the proposed algorithm have verified by some experimental results to express an improved performance compared to the N-cut algorithm. Also the significant reduction to the computational cost of the proposed algorithm in the experiments is favourable for practical applications. The experimental results reported in this research work are very promising, resulting in very high classification accuracies, and demonstrate the efficacy of the proposed system for addressing the problem of small sample size as well as mixed pixel conditions. In the future, we will also develop computationally efficient implementations of the proposed approaches by resorting to parallel computer architectures. We want to create for fast convergence of the algorithm for hyper spectral image segmentation.

References

[1] Ji, R, Gao, Y, Hong, R, Liu, Q, Tao, D, Li, X., "Spectral-Spatial Constraint Hyper spectral Image Classification"Geoscience and Remote Sensing, IEEE Transactions on 2013 (Volume:PP , Issue: 99) Page(s):1

[2] Qingyan Wang, Junping Zhang, Jiawei Chen, Ye Zhang "An improved spectral reflectance and derivative feature fusion for hyper spectral image classification" Geoscience and Remote Sensing Symposium (IGARSS), 2011 IEEE International, Page(s):1696 – 1699.

[3] Minshan Cui, Prasad, S, Bruce, L.M, Shrestha, R, "Robust spatial-spectral hyper spectral image classification for vegetation stress detection", Geoscience and Remote Sensing Symposium (IGARSS), IEEE International 2012, Page(s):5486 – 5489.

[4] Bezdek, James C., L. O. Hall, and L_P Clarke. "Review of MR image segmentation techniques using pattern recognition." *Medical physics* 20.4 (1992): 1033-1048.

[5] Skarbek, Wladyslaw, Andreas Koschan, and Zur Veroffentlichung. "Colour image segmentation-a survey." (1994).

[6] Haralick, Robert M., and Linda G. Shapiro. " Image segmentation techniques." Computer vision, graphics, and image processing 29.1 (1985): 100-132.

[7] J.Schiewe, Segmentation of High-Resolution Remotely Sensed Data-Concepts, Applications and Problems, Symposium On Geospatial Theory, Processing And Applications, Ottawa, 2002

[8] Yanfeng Gu, Ying Liu, Ye Zhang, "A Soft Classification Algorithm based on Spectral-spatial Kernels in Hyper spectral Images", Innovative Computing, Information and Control, ICICIC '07, Second International Conference on 2007, Page(s):548.

BIOGRAPHIES

Dr. S. Thavamani is an Associate Professor in Department of Computer Applications, SNR Sons College, Coimbatore, Tamil Nadu, India. She has a teaching experience of 17 years in the field of Computer science. Her area of Specialization is Distributed Computing and P2P Networks. She has presented more than 15 Papers in various International and National Conferences and she has published 7 international Journals. She is currently a supervisor for M.Phil. research works of various Universities. She completed Ph.D., Degree in SNR Sons College, under Bharathiar University, Coimbatore.