ISSN 2229-5518

Comparison of Various Classification Techniques for Satellite Data

[1]Manoj Pandya, [1]Astha Baxi, [1]M.B. Potdar, [1]M.H. Kalubarme, [2]Bijendra Agrawal

Abstract - Computer interpretation of remote sensing data is referred to as quantitative analysis because of its ability to identify pixels based upon their numerical properties and owing to its ability for counting pixels for area estimates. It is also generally called classification, which is a method by which labels may be attached to pixels in view of their spectral character. This labeling is implemented by a computer by having trained it beforehand to recognize pixels with spectral similarities. Clearly the image data for quantitative analysis must be available in digital form. This is an advantage with image data types, such as that from Landsat, SPOT, IRS, etc, as against more traditional aerial photographs. The latter require digitization before quantitative analysis can be performed. Various classification techniques adopted in this study include unsupervised classifiers like K-Means, ISODATA and supervised classifiers like Minimum Distance, Maximum Likelihood Classifier, Parallelpiped and Enhanced Seeded region Growing Technique.

Index Terms – Satellite Data, Classification, supervised, unsupervised, K-Means, ISODATA, MXL, Prallelpiped, Seeded Region Growing

1. INTRODUCTION

Satellite imagery is a source of large amount of information. A two dimensional image that is recorded by satellite sensors is the mapping of the three dimensional visual world. The captured two dimensional signals are sampled and quantized to yield digital images. An Image is worth a thousand words. Satellite image interpreters from various domains extract Information by marking polygon features on image. Various classification methods facilitate to automatically classify objects from image. There are several methods which can be used to extract features.

2. IMAGE SEGMENTATION

Segmentation of an image is defined by a set of regions that are connected and non-overlapping, so that each pixel in a segment in the image acquires a unique region label that indicates the region it belongs to. Segmentation is one of the most important elements in automated image analysis, mainly because at this step the objects or other entities of interest are extracted from an image for subsequent processing, such as description and recognition.

- Manoj Pandya, Astha Baxi, M.B. Potdar & M.H. Kalubarme are currently affiliated with Bhaskaracharya Institute for Space Applications and Geo-Informatics (BISAG), Gandhinagar, Gujarat, India PIN 382007 E-mail: mjpandya@yahoo.com
- Dr. Bijendra Agrawal is Director, VJKMSGroup of institutions, VADU, Kadi, Mahesana, Gujarat, India

3 CLASSIFICATION METHODS

There are basically two kinds of classification methods. Unsupervised and supervised.

Unsupervised Classifiers:

These kinds of classifiers don't require training site or training resources to classify objects.

K-MEANS

In statistics and data mining, k-means clustering is a method of cluster analysis which aims to partition n observations into k clusters in which each observation belongs to the cluster with the nearest mean.

It is an iterative procedure.

- In first step, it assigns an arbitrary initial cluster vector.
- The second step classifies each pixel to the closest cluster.
- In the third step the new cluster mean vectors are calculated based on all the pixels in one cluster.

- The second and third steps are repeated until the "change" between the iteration is small. The "change" can be defined in several different ways; either by measuring the distances the mean cluster vector has changed from one iteration to another or by the percentage of pixels that have changed between iterations.
- The objective of the k-means algorithm is to minimize the within cluster variability. The objective function (which is to be minimized) is:

Sums of squares distances (errors) between each pixel and its assigned cluster centre.

$$SS_{\text{distances}} = \sum_{\forall x} \left[x - C(x)\right]^2 \quad 1$$

Where, C(x) is the mean of the cluster that pixel x is assigned to.

Minimizing the SSdistances is equivalent to minimizing the Mean Squared Error (MSE). The MSE is a measure of the within cluster variability.

$$MSE = \frac{\sum_{\forall x}\left[x - C(x)\right]^2}{(N-c)b} = \frac{SS_{\text{distances}}}{(N-c)b} \quad 2$$

ISO Data (Iterative Self-Organizing) Classifier

ISO Data stands for Iterative Self-Organizing Data Analysis Techniques. This algorithm allows the number of clusters to be automatically adjusted during the iteration by merging similar clusters and splitting clusters.

Clusters are merged if either the number of members (pixel) in a cluster is less than a certain threshold or if the centres of two clusters are closer than a certain threshold. Clusters are split into two different clusters if the cluster standard deviation exceeds a predefined value and the number of members (pixels) is twice the threshold for the minimum number of members. [1]

The ISODATA algorithm is similar to the k-means algorithm with the distinct difference that the ISODATA algorithm allows for different number of clusters while the k-means assumes that the number of clusters is known a priori.

- Each pixel is compared to each cluster mean and assigned to the cluster whose mean is closest in Euclidean distance.

$$\sqrt{(DN_{b1i} - DN_{b1m})^2 + \ldots + (DN_{bxi} - DN_{bxm})^2} \quad 3$$

- A new cluster center is computed by averaging the locations of all the pixels assigned to that cluster.
- The Sum of Squared Errors (SSE) computes the cumulative squared difference (in the various bands) of each pixel from its cluster center for each cluster individually, and then sums these measures over all the clusters.
- The algorithm will stop either when the # iteration threshold is reached or the max % of unchanged pixel threshold is reached

Supervised Classifiers:

These kinds of classifiers require adequate training sites or training signatures for each class of a given image.

Minimum Distance Classifier

This classifier is also referred to as central classifier. This classifier is the simplest classifier.

- Analyst first computes mean of each training class.
- Next the distance (Euclidian) of each pixel from the mean is calculated.
- The pixel is assigned to that class whose distance is nearest to the mean (i.e. the Euclidian distance is minimum between the pixel and the mean).

The distance is defined as an index of similarity so that the minimum distance is identical to the maximum similarity. Figure 1 shows the concept of a minimum distance classifier. The following distances are often used in this procedure. [7]

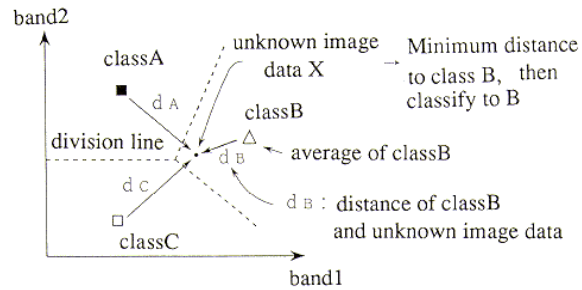

Figure 1: Minimum Distance Classifier

It is used to classify unknown image data to classes which minimize the distance between the image data and the class in multi-feature space.

In the Euclidean plane, if p = (p1, p2) and q = (q1, q2) then the distance is given by

$$d(p, q) = \sqrt{(p_1 - q_1)^2 + (p_2 - q_2)^2}. \quad 4$$

Fig: 1 Schema for feature tables using pre-defined data types

Parallel Piped Classifier:

The parallelepiped classifier (often termed multi-level slicing) divides each axis of multi-spectral feature space, as shown in an example in Figure 2

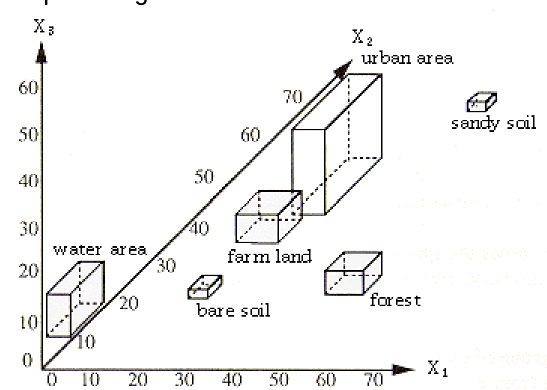

Figure 2: Schematic concept of parallel piped classifier in three dimensional feature spaces

The decision region for each class is defined on the basis of a lowest and highest value on each axis. The accuracy of classification depends on the selection of the lowest and highest values in consideration of the population statistics of each class. In the two-dimensional feature space this forms a rectangular box. We can have as many boxes as number of classes. All the data points which fall within the box are labeled to that class. In this respect, it is most important that the distribution of population of each class is well understood. [2]

Maximum Likelihood Classifier (MXL):

The maximum likelihood classifier is one of the most popular methods of classification in remote sensing, in which a pixel with the maximum likelihood is classified into the corresponding class. The likelihood Lk is defined as the posterior probability of a pixel belonging to class k. [4]

Lk = P(k)*P(X/k) / P(i)*P(X/i) 5

where P(k) : prior probability of class k

P(X/k) : conditional probability to observe X from class k, or probability density function

Usually P(k) are assumed to be equal to each other and P(i)*P(X/i) is also common to all classes.

Therefore Lk depends on P(X/k) or the probability density function.

For mathematical reasons, a multivariate normal distribution is applied as the probability density function. In the case of normal distributions, the likelihood can be expressed as follows. [5]

$$L_k(X) = \frac{1}{\sqrt{(2\pi)^n |\Sigma_k|}} e^{\left(\frac{-1}{2}\right)(X - x_k)^T \Sigma^{-1} (X - x_k)} \qquad 6$$

Where,

n: number of bands

X: image data of n bands

Lk(**X**) : likelihood of **X** belonging to class k

Xk : mean vector of class k

Σ_k : **variance-covariance matrix** of class k

$|\Sigma_k|$ is determinant of Σ_k

In the case where the variance-covariance matrix is symmetric, the likelihood is the same as the Euclidian distance.

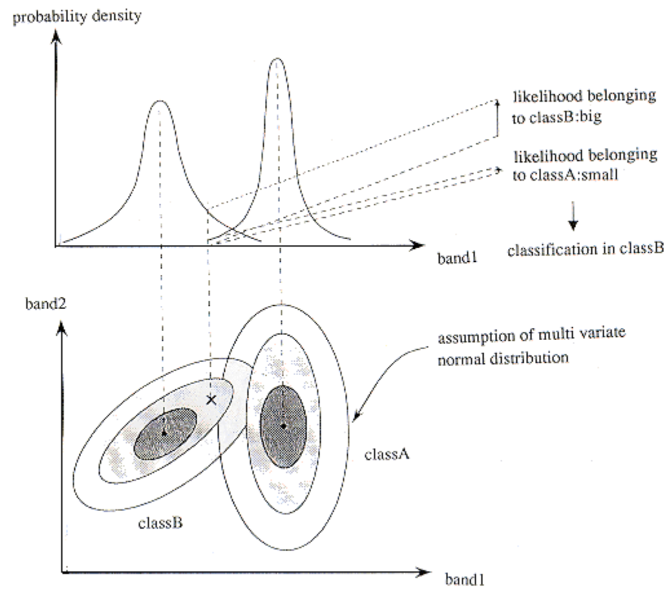

Figure 3: concept of the maximum likelihood method

Seeded Region Growing Technique:

Seed point selection is based on some user criterion like pixels in a certain gray-level range, pixels evenly spaced on a grid, etc. An image is segmented into regions with respect to a set of q seeds. Given the set of seeds, S1, S2, . . . , Sq, each step of SRG involves one additional pixel to one of the seed sets. Moreover, these initial seeds are further replaced by the centroids of these generated homogeneous regions, R1, R2, ... , Rq, by involving the additional pixels step by step. The pixels in the same region are labeled by the same symbol and the pixels in variant regions are labeled by different symbols. All these labeled pixels are called the allocated pixels, and the others are called the unallocated pixels. Let H be the set of all unallocated pixels which are adjacent to at least one of the labeled regions. [14]

$$H = \left\{ (x, y) \notin \bigcup_{i=1}^{q} [R_i \;\middle|\; N(x, y) \cap \bigcup_{i=1}^{q} R_i \neq \emptyset] \right\} \qquad 7$$

Where, N(x, y) is the second-order neighborhood of the pixel (x, y) as shown in Figure 1. For the unlabeled pixel (x, y) ϵ H, N(x, y) meets just one of the labeled image region Ri and define $\phi(x, y) \in \{1, 2, ..., q\}$ to be that index such that $N(x, y) \cap R_{\phi(x,y)} \neq \phi$. $\delta(x, y, R_i)$ is defined as the difference between the testing pixel at (x, y) and its adjacent labeled region R_i. $\delta(x, y, R_i)$ is calculated as

$$\delta(x, y, R_i) - \left| g(x, y) - g(X_i^c, Y_i^c) \right| \qquad 8$$

Where g(x, y) indicates the values of the three color components of the testing pixel (x, y), g (X^{c}_{i} , Y^{c}_{i}) represents the average values of three colors components of the homogeneous region R_i, with g(X^{c}_{i} , Y^{c}_{i}) the centroid of R_i.

(x-1, y-1)	(x, y-1)	(x+1, y-1)
(x-1, y)	(x, y)	(x+1, y)
(x-1, y+1)	(x, y+1)	(x+1, y+1)

Figure 4: identification of pixels around the seed pixel

If N(x, y) meets two or more of the labeled regions, ϕ(x, y) takes a value of i such that N(x, y) meets R_i and δ(x, y, R_i) is minimized.

$$\emptyset(x, y) = \min_{(x,y)\in H} \{\delta(x, y, R_j)\ j \in \{1, \ldots, q\}\} \quad 9$$

This seeded region growing procedure is repeated until all pixels in the image have been allocated to the corresponding regions.

Enhanced Seeded Region Growing:

This technique was specifically designed by Baxi et al., 2012, for mobile applications along with mahalanobis distance classifier [16]. SRG is also very attractive for semantic image segmentation by involving the high-level knowledge of image components in the seed selection procedure.

The location information with metadata is considered as seed points which can be super-imposed on the geog-referenced image using Application Programming Interface (API). These seed points generate training sites for SRG technique

Enhanced Classifier:

The distance of pixel from the mean of given class is calculated by variance and co-variance methods. It differs from Euclidean distance in that it takes into account the correlations of the data set and is multivariate effect size.

$$d_k^2 = (X - X_k)^T \Sigma_k^{-1} (X - X_k) \quad 10$$

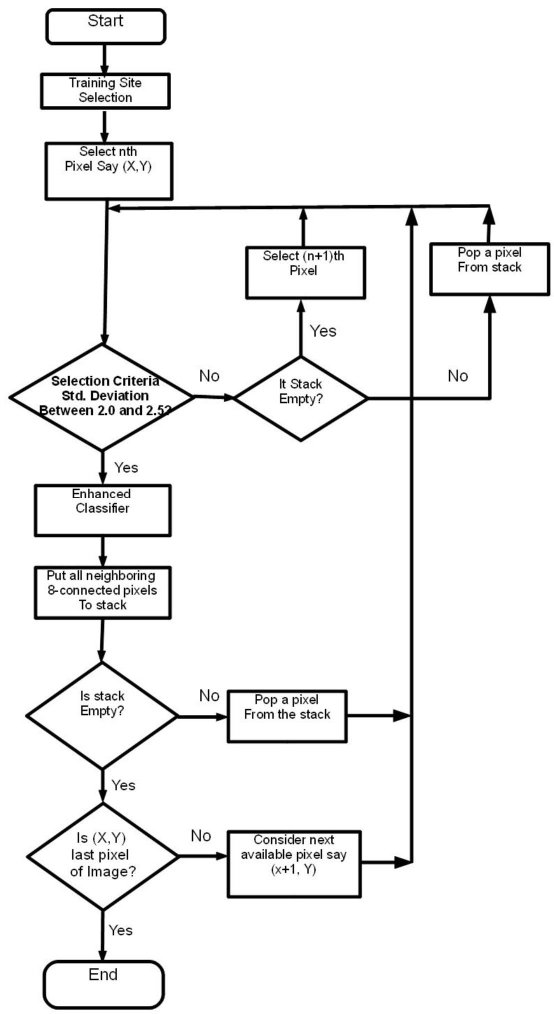

Figure 5: Methodology for ESRG Classifier

where **X** : vector of image data (n bands)
X = [x1, x2, ... xn]
Xk : mean of the kth class
Xk = [m1, m2, ... mn]

σk : variance matrix

$$\sigma_k = \begin{bmatrix} \sigma_{11} & 0 & \cdots & 0 \\ 0 & \sigma_{22} & & 0 \\ \vdots & & \ddots & \\ 0 & \cdots & \cdots & \sigma_{nn} \end{bmatrix}$$

Σk : variance-covariance matrix

$$\Sigma_k = \begin{bmatrix} \sigma_{11} & \sigma_{12} & \cdots & \sigma_{1n} \\ \sigma_{21} & \sigma_{22} & \cdots & \sigma_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ \sigma_{n1} & \sigma_{n2} & \cdots & \sigma_{nn} \end{bmatrix}$$

4 COMPARISONS OF CLASSIFIERS

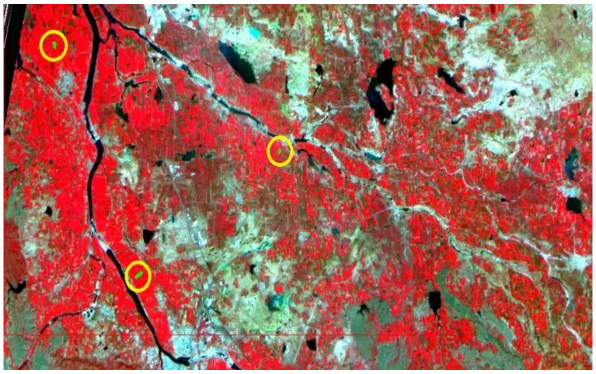

Figure 6 (a) FCC LISS 3 Image of Surendranagar district India with Cotton Seeds marked in yellow circles

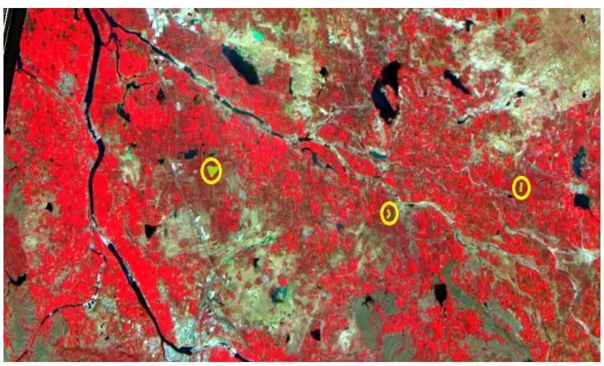

Figure 6 (b) Paddy Seeds in yellow circles

As shown in the above figure 6(a), a satellite image Linear Image Self Scan 3 (LISS 3) is taken with cotton seeds marked in yellow circle. Figure 6(b) shows Paddy seeds in yellow circles. Figure 7 shows the classified figure where cotton is in red and paddy is in green colour.

CLASSIFIED IMAGE

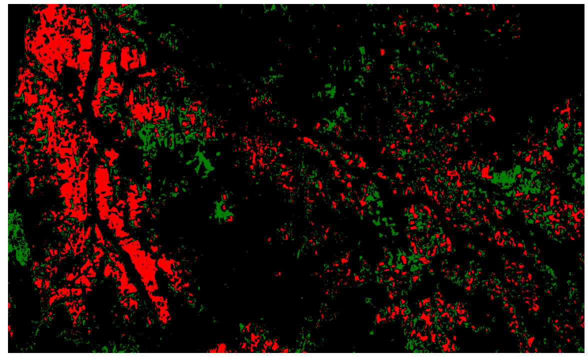

Figure 7: Enhanced SRG for both classes

ACCURACY ASSESSMENT

Kappa coefficient is used to evaluate the accuracy. The original intent of Cohen's Kappa was to measure the degree of agreement or disagreement of two or more people observing the same phenomenon. Cohen's kappa measures the agreement between two raters who each classify N items into C mutually exclusive categories. The equation for K is:

$$K = Pr(a) - Pr(e)/1 - Pr(e) \qquad 11$$

Where Pr(a) is the relative observed agreement among raters or the total agreement probability, and Pr(e) is the hypothetical probability of chance agreement, using the observed data to calculate the probabilities of each observer randomly saying each category. If the raters are in complete agreement then K = 1. If there is no agreement among the raster, then $K \leq 0$. The better performing classifiers should then have the higher K.

Table 1: Comparison of various classifiers

Parameters	k-means	ISO Data	Minimum Distance	Parallel Piped	Maximum Likelihood	SRG	ESRG
Method	Unsupervised	Unsupervised	Supervised	Supervised	Supervised	Supervised	Supervised
Distance	Euclidean Mean	Euclidean Mean	Euclidean Mean	Std. Deviation	Std. Deviation	Euclidean Mean	Std. Deviation
Complexity	Low	Low	Low	Medium	High	Medium	Medium
Accuracy	Low	Low	Low	Medium	High	Medium	High
Advantages	Simple process and fast to execute	successful at finding inherent spectral clusters	Simple process and easy to execute	Simple process and easy to execute	Efficient method to classify objects	Only Seed points instead of training site marking is required	Seed points can be marked at field level with class details Classifies even for less training sites
Drawbacks	Analyst doesn't know a priori number of spectral classes	Analyst doesn't know a priori number of spectral classes iterations can be time consuming	Accuracy is less as it considers only the mean	Box of each class can overlap to others which may produce false result	Sufficient ground truth data required otherwise output results in failure Process can be time consuming	Sufficient ground truth data required otherwise output results in failure	Process can be time consuming
Kappa	0.5895	0.5987	0.6141	0.6718	0.7512	0.6676	0.8143

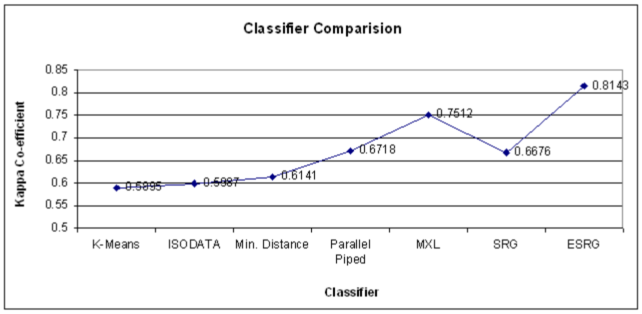

Figure 8: Classifier vs. Kappa co-efficient chart

As shown is the above figure 8, the accuracy for ESRG is higher than other classifiers that reaches to 0.81 i.e. 81 %

5 CONCLUSIONS

Various Classification techniques for satellite images have different accuracy. Hybrid method of SRG and Mahalanobis technique leads to better accuracy.

The extension to the ESRG classifier is Artificial Neural Network (ANN) and Fuzzy logic. Object oriented classification also leads to precisely identify objects like trees, car, buses etc.

ACKNOWLEDGEMENTS

The authors would like to thank to the Director, BISAG, T .P. Singh for his inspiration and motivation.

REFERENCES

[1] http://www.yale.edu/ceo/Projects/swap/landcover/Unsupervised_classification.htm

[2] Parallel Piped Classifier "http://stlab.iis.u-tokyo.ac.jp/~wataru/lecture/rsgis/rsnote/cp11/11-4-1.gif"

[3] Variance "www.stat.yale.edu/~pollard/Courses/241.fall97/Variance.pdf"

[4] Maximum Likelihood http://stlab.iis.u-tokyo.ac.jp/~wataru/lecture/rsgis/rsnote/cp11/cp11-7.htm

[5] http://edndoc.esri.com/arcobjects/9.2/net/shared/geoprocessing/spatial_analyst_tools/how_maximum_likelihood_classification_works.htm

[6] Mahabolis_Dist.txt http://research.cs.tamu.edu/prism/lectures/iss/iss_l12.pdf

[7] Joseph, George (2003) Fundamentals of Remote Sensing ISBN: 81 7371 457 6

[8] Ahmed Rekik, Mourad Zribi, et al. An Optimal Unsupervised Satellite image Segmentation Approach Based on Pearson System and k-Means Clustering Algorithm Initialization

[9] Tobler, W. R. "A classification of map projections", *Annals of the Association of American Geographers*, Vol. 52, pp. 167-175.

[10] Sergio Bernabé, Antonio Plaza, A New Tool for Classification of Satellite Images Available from Google Maps: Efficient Implementation in Graphics Processing Units

[11] Piscataway, NJ: IEEE, Knowledge-based semi-supervised satellite image classification

[12] Aykut AKGÜNa,, A.Hüsnü ERONAT, et at. Comparing Different Satellite Image Classification Methods: An Application In Ayvalik District,Western Turkey

[13] Frank Y. Shih, Shouxian Cheng,Computer Vision Laboratory, College of Computing Sciences, New Jersey Institute of Technology, Newark, NJ 07102, USA,Automatic seeded region growing for color image segmentation (2005)

[14] Jianping Fan a, Guihua Zeng Frank Y. Shih, et al. , Seeded region growing: an extensive and comparative study

[15] http://en.wikipedia.org/wiki/Region_growing

[16] Astha Baxi, Manoj Pandya, M .H. Kalubarme and M .B. Potdar,2012. Supervised Classification of Satellite Imagery using Enhanced Seeded Region Growing Technique

[17] Jianping Fan, Guihua Zeng , Mathurin Body , Mohand-Said Hacid, "Seeded region growing: an extensive and comparative study", Elsevier B.V. , Pattern Recognition Letters 26 , 2005

[18] Rolf Adams and Leanne Bischo, "Seeded region growing", IEEE transactions on pattern analysis and machine intelligence, vol. 16, no. 6, June 1994