CHAPTER 8

8 MODELLING AND IMPLEMENTATION

Human analyst is unable to discriminate to the limit of the radiometric resolution generally available. By comparison if a computer can be used for analysis, it could conceivably do so at the pixel level and could examine and identify as many pixels as required. In addition, it should be possible for computer analysis of remote sensing image data to take full account of the multidimensional aspect of the data including its full radiometric resolution.

8.1 Comparison of various classifiers:
Table 8.1: Comparison of various classifiers

<table>
<thead>
<tr>
<th>Parameters</th>
<th>k-means</th>
<th>ISO Data</th>
<th>Minimum Distance</th>
<th>Parallel Piped</th>
<th>Maximum Likelihood</th>
<th>SRG</th>
</tr>
</thead>
<tbody>
<tr>
<td>Method</td>
<td>Unsupervised</td>
<td>Unsupervised</td>
<td>Supervised</td>
<td>Supervised</td>
<td>Supervised</td>
<td>Supervised</td>
</tr>
<tr>
<td>Distance</td>
<td>Euclidean Mean</td>
<td>Euclidean Mean</td>
<td>Euclidean Mean</td>
<td>Std. Deviation</td>
<td>Std. Deviation</td>
<td>Euclidean Mean</td>
</tr>
<tr>
<td>Complexity</td>
<td>Low</td>
<td>Low</td>
<td>Low</td>
<td>Medium</td>
<td>High</td>
<td>Medium</td>
</tr>
<tr>
<td>Accuracy</td>
<td>Low</td>
<td>Low</td>
<td>Low</td>
<td>Medium</td>
<td>High</td>
<td>Medium</td>
</tr>
<tr>
<td>Advantage</td>
<td>Simple process and fast to execute</td>
<td>successful at finding inherent spectral clusters</td>
<td>Simple process and easy to execute</td>
<td>Simple process and easy to execute</td>
<td>Efficient method to classify objects</td>
<td>Only Seed points instead of training site marking is required</td>
</tr>
<tr>
<td>Drawbacks</td>
<td>Analyst doesn't know a priori number of spectral classes</td>
<td>iterations can be time consuming</td>
<td>Accuracy is less as it considers only the mean</td>
<td>Box of each class can overlap to others which may produce false result</td>
<td>Sufficient ground truth data required otherwise output results in failure</td>
<td>Sufficient ground truth data required otherwise output results in failure</td>
</tr>
</tbody>
</table>

Computer interpretation of remote sensing image 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.

8.2 Literature Survey Findings

The comparison among various classification methods comprises different methods to classify objects from the satellite imagery. The comparison shown in the above table represents that Maximum Likelihood classifier has higher accuracy compared to other classifiers. However, there are certain constraints like requirement of sufficient number of signature sites; dependency on other parameters requires an expert analyst observation while generating training sites. The method can result in failure in case of less number of training sites and minor errors within training signature.

8.2.1 Research Problem Formulation

SRG by its name requires only a seed point compared to a complete training signature made of polygon by the collection of various points. The existing SRG methodology suffers from certain drawbacks like less accuracy, locating the site on image by latitude and longitude etc. This leads to propose a new classifier to modify or enhance the existing method to improve not only the performance but also to provide easy, flexible mechanism to classify objects.

8.3 Proposed Model: Enhanced Seeded Region Growing (ESRG)

Enhanced Seeded Region Growing (ESRG) is a proposed classifier. To overcome the drawbacks of existing SRG classifier, a methodology is proposed to take near real time training sites from the ground field by the survey analyst himself through GPS enabled cell phone devices.
Enhanced or modified Seeded Region Growing (ESRG) Classifier requires less training signatures and these training signatures are based on data centric approach rather than manually marking seed points through an analyst. ESRG classifier considers the entire image as it is class based classifier rather than only considering the region.

Table 8.2: difference between SRG and ESRG

<table>
<thead>
<tr>
<th></th>
<th>SRG</th>
<th>ESRG</th>
</tr>
</thead>
<tbody>
<tr>
<td>It requires seed points per bounded regions.</td>
<td>It requires seed points per class.</td>
<td></td>
</tr>
<tr>
<td>Seed selection procedure is dependent on data collected by ground truth survey. It is required to insert this data in system by a person.</td>
<td>Seed selection procedure is through GPS Enabled cell phone device. As soon as the person collects data from ground truth survey, information can be inserted in the centralized server.</td>
<td></td>
</tr>
<tr>
<td>Requires large amount of seed points to classify the entire image.</td>
<td>Requires fewer seed points to classify entire image.</td>
<td></td>
</tr>
<tr>
<td>It may not consider the entire image.</td>
<td>It considers the entire image.</td>
<td></td>
</tr>
<tr>
<td>Region Based Object Selection</td>
<td>Class Based object selection</td>
<td></td>
</tr>
<tr>
<td>Seeded region selection and object classification method uses same threshold value.</td>
<td>Seeded region selection uses threshold and object classification method uses standard deviation.</td>
<td></td>
</tr>
</tbody>
</table>

8.3.1 Materials (Resources):

**Satellite Image:** The image which is to be classified

**GPS Enabled Mobile Device:** The mobile device having capability to capture location of the site in terms of latitude and longitude. The Mobile device (cell phone) is used to transmit the information gathered at the field and send to the Intermediate stage.

**GSM Modem or Gateway service:** Receives information in the form of SMS, translates into comma separated value and inserts into database server.
Figure 8.1: Flow diagram for ESRG
Use of GEO ICT can be converged in image classification process to generate seed points. The GPS enabled mobile devices cell phone devices or integrated GPS cell phone devices can be used to collect feature details and position of the location. The location details are transmitted to the centralized server at the time of ground survey in the form of GEO SMS using GSM modem or Gateway services protocols. The server fetches corresponding information and stores in the database.

**Figure 8.2: Use of GEO ICT in the seed pixel based image data classification**

The location information with metadata is considered as seed points which can be superimposed on the geog-referenced image using Application Programming Interface (API). These seed points generate training sites for SRG technique. All images taken from the same path on that particular day can be classified using this method. Once the signature data is collected, the image can be classified by the following steps:
8.4 Transformation of Proposed Model into Prototype Model

(Procedure):

1. Select the area of interest (AOI) from the image, which is to be classified. The entire image can also be treated as AOI.

2. The starting pixel of AOI is denoted as $S_t(X, Y)$. If the width of AOI is say $W$ and height is $H$ then define an array list of size $A[W, H]$ and initialize it as $A[i, j]=0$ for every $i \leq W, j \leq H$ and $i, j \geq 0$.

3. Now plot all the signature sites (training sites) on the image and store its equivalent pixel’s intensity values.

4. Find the mean of these intensity values. Say, $I$.

5. Find the mean of these intensity values. Say, $I$ and standard deviation (S.D. $\sigma$)

$$
\sigma = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (x_i - \bar{x})^2}
$$

Where $\bar{x}$ = mean of intensity value

6. Define a stack- single dimension array list, Say $S$ of some size. Here stack size is defined to overcome the stack overflow problem. For better performance, machines having higher memory are recommended as it is required to limit the stack size.

7. Now start with the pixel $S_t(X, Y)$. The intensity of $S_t(X, Y)$ is say, $\bar{i}$. If $S_t(X, Y)$ is not labelled and $|I - \bar{i}| \leq 3$ of S.D and probability of pixel belonging to a class is greater than 2% then mark $A[i, j]$ as labelled. Find its 8-connected neighbouring pixels and push them in $S$ if $S$ is not full. If $S$ is full then leave the neighbouring pixels unlabeled. If $S_t(X,Y)$ is not labelled and $|I - \bar{i}| > T$ then take the next available pixel in AOI, say $(X+1,Y)$ and repeat step 7.
8. If S is not empty then pop a pixel and find its intensity. Continue the same process as described in step 7 until S is empty. If S is empty then go to the next available pixel in AOI, say (X+1, Y) and repeat the same procedure described in step 7.

9. Continue this procedure until the entire AOI is covered.

The stack used here is a simple stack concept of C language. It uses last in first out concept. So it is an array which is bounded on a single side. The pixels are stored in array i.e. push inside stack and then one by one pixels are taken out from an array i.e. pop from the stack. Once the pixels are popped it is no longer stored inside the array. So in this algorithm the neighboring pixels are stored inside the array i.e. pushed inside the stack and then after one pixel is done it’ll fetch another neighboring pixel from the array i.e pop from the stack and again check its intensity values.

Here, the efficiency of this algorithm depends upon factors like Signature sites, clarity of the image to be classified, T, size of S and the time difference between the ground truth collection and satellite acquisition of the data.

The probability of a pixel belonging to a class is calculated by mahalanobis distance. It differs from Euclidean distance in that it takes into account the correlations of the data set and is multivariate effect size.

The advantage of the Mahalanobis classifier over the maximum likelihood procedure is that it is faster and yet retains a degree of direction sensitivity via the covariance matrix \( \Sigma \), which could be a class average or a pooled variance [361].

\[
d_k^2 = (X - X_k)^T \Sigma_k^{-1} (X - X_k)
\]

where \( X \) : vector of image data (n bands)
\( X = [ x_1, x_2, ..., x_n ] \)
\( X_k \) : mean of the kth class
\( X_k = [ m_1, m_2, ..., m_n ] \)
\[ \sigma_k : \text{variance matrix} \]
\[ \begin{bmatrix}
\sigma_{11} & 0 & \cdots & 0 \\
0 & \sigma_{22} & \cdots & 0 \\
\vdots & \vdots & \ddots & \vdots \\
0 & \cdots & \cdots & \sigma_{nn}
\end{bmatrix} \]

\[ \Sigma_k : \text{variance-covariance matrix} \]
\[ \begin{bmatrix}
\sigma_{11} & \sigma_{12} & \cdots & \sigma_{1n} \\
\sigma_{21} & \sigma_{22} & \cdots & \sigma_{2n} \\
\vdots & \vdots & \ddots & \vdots \\
\sigma_{n1} & \sigma_{n2} & \cdots & \sigma_{nn}
\end{bmatrix} \]

**Mahalanobis Distance:**

It is based on correlations between variables by which different patterns can be identified and analyzed. It gauges similarity of an unknown sample set to a known one. It differs from Euclidean distance in that it takes into account the correlations of the data set.

**Figure 8.3: Mahalanobis distance**

The above graph shows simulated bivariate normal data that is overlaid with prediction ellipses. The ellipses in the graph are the 10% (innermost), 20%, ..., and 90% (outermost) prediction ellipses for the bivariate normal distribution that generated the data. The prediction ellipses are contours of the bivariate normal density function. The probability density is high for ellipses near the origin, such as the 10% prediction ellipse. The density is low for ellipses are further away, such as the 90% prediction ellipse [308].

In the above figure 8.3, two observations are displayed by using red stars as markers. The first observation is at the coordinates (4,0), whereas the second is at (0,2). The question
is: which marker is closer to the origin? (The origin is the multivariate center of this distribution.)

The answer is, "It depends how you measure distance." The Euclidean distances are 4 and 2, respectively, so you might conclude that the point at (0,2) is closer to the origin. However, for this distribution, the variance in the Y direction is less than the variance in the X direction, so in some sense the point (0,2) is "more standard deviations" away from the origin than (4,0) is.

*Note:

Writing the transpose of the matrix of cofactors, known as an adjugate matrix, can also be an efficient way to calculate the inverse of small matrices, but this recursive method is inefficient for large matrices. To determine the inverse, we calculate a matrix of cofactors:

\[
A^{-1} = \frac{1}{|A|} (C^T)_{ij} = \frac{1}{|A|} \begin{pmatrix}
C_{11} & C_{21} & \cdots & C_{n1} \\
C_{12} & C_{22} & \cdots & C_{n2} \\
\vdots & \vdots & \ddots & \vdots \\
C_{1n} & C_{2n} & \cdots & C_{nn}
\end{pmatrix}
\]

Where |A| is the determinant of A, C_{ij} is the matrix of cofactors, and C^T represents the matrix transpose.

**Matrix of Co-factors:**

The matrix of cofactors for an \( n \times n \) matrix \( A \) is the matrix whose \((i,j)\) entry is the cofactor \( C_{ij} \) of \( A \). For instance, if \( A \) is
Inversion of $2 \times 2$ matrices can be done as follows:

$$A^{-1} = \begin{bmatrix} a & b \\ c & d \end{bmatrix}^{-1} = \frac{1}{\text{det}(A)} \begin{bmatrix} d & -b \\ -c & a \end{bmatrix} = \frac{1}{ad - bc} \begin{bmatrix} d & -b \\ -c & a \end{bmatrix}$$

Where determinant of $A$ det $(A)$ can be denoted by:

$$\text{det} (A) = ad - bc$$

Inversion of $3 \times 3$ matrices can be done as follows:

$$A^{-1} = \begin{bmatrix} a & b & c \\ d & e & f \\ g & h & k \end{bmatrix}^{-1} = \frac{1}{\text{det}(A)} \begin{bmatrix} A & B & C^T \\ D & E & F \\ G & H & K \end{bmatrix} = \frac{1}{\text{det}(A)} \begin{bmatrix} A & D & G \\ B & E & H \\ C & F & K \end{bmatrix}$$

Where determinant of $A$ det $(A)$ can be denoted by:

$$\text{det}(A) = a(ek - fh) + b(fg - kd) + c(dh - eg)$$