CHAPTER 5

SEGMENTATION AND CLUSTERING

5.1. INTRODUCTION

Image segmentation is one of the vital techniques used in digital image processing for partitioning an image into multiple segments. Image segmentation is performed to locate objects and boundaries in images. It is very much helpful in finding more meaningful representations about the image. It is used to analyze the image to extract detailed information about the landscapes, earth resources, weather monitoring, climatic changes, environmental pollutions and agricultural yields are few among them. Applications of segmentation are numerous, and it is most widely used in the following areas namely, medical imaging, object identification in satellite images, different types of pattern recognition systems like face, iris and finger print for security systems, agriculture image for crop disease detection and so on.

In this chapter, the enhanced satellite image is segmented and clustered it into six different color regions, based on the reflectance of the earth’s surface. This research work proposed an algorithm called as “Amalgamation of Mean shift (k-means), with Watershed transform and Morphological operations” (AMWM) algorithm. The mean shift algorithm (k-means) segments the satellite images into closed region boundaries and gives solid results, by automatically separating the image into six colored clusters. Watershed transform is a segmentation method based on color regions, which classifies
pixels in the given image according to their spatial proximity (nearness), the gradient of their gray levels and the homogeneity of their textures. Finally, morphological operations like dilation and erosion are applied on the image to separate the connected objects. This proposed algorithm removes the drawbacks such as (i) sensitivity to noise and (ii) reduces the over-segmentation in the images.

5.2. HUMAN VISION - GROUPING AND GESTALT

The Gestalt school of psychologists emphasizes the grouping as an important part of understanding human vision [PAL, 90]. A common experience of segmentation is the way that, an image can resolves itself into a figure, as an important object such as foreground and background on which the image lies.

The Gestalt school uses the concept of a gestalt — a whole or a group — and the set of internal relationships that makes it a whole as central components in their ideas. Their work was distinguished by efforts to write down a series of rules by which image elements would be associated together and interpreted as a group.

The Gestalt psychologists identified a series of factors, which they felt predisposed a set of elements to be grouped. There are a variety of features, some of which refers the main Gestalt movement:

- **Proximity**: tokens those are nearby likely to be grouped.
- **Similarity**: similar tokens are likely to be grouped together.
- **Common fate**: tokens that have logical motion tend to be grouped together.
- **Common region**: tokens that lie inside the same closed region be likely to be grouped together.
- **Parallelism**: parallel curves or tokens are likely to be grouped together.
- **Closure**: tokens or curves that are likely to lead to closed curves have a tendency which will be grouped together.
- **Symmetry**: curves that lead to symmetric groups are grouped together.
• *Continuity*: tokens that lead to “continuous” — as in “joining up nicely”, rather than in the formal sense — curves tend to be grouped.

• *Familiar Configuration*: tokens that, when grouped, direct to a recognizable object, be likely to be grouped together.

### 5.3. IMAGE SEGMENTATION

Image segmentation is an essential process for most image analysis tasks aiming at decomposing an image into regions having visual similarity. It is a process to seek out for homogenous regions in an image and classifying these regions. In other words, it can also be defined as, “the partitioning of an image into a meaningful regions based on homogeneity or heterogeneity criteria” [HAR, 92]. Image segmentation techniques can be categorized into pixel-oriented, contour-oriented, region-oriented, model-oriented, color-oriented and hybrid-oriented.

Color image segmentation is a vital process in image analysis and is widely used in computer vision, image interpretation and pattern recognition systems. Its applications extent in scientific and industrial fields such as medical image analysis, remote sensing, microscopy, content-based image and video retrieval, document analysis, industrial automation and quality control [RIC, 08]. The performance of color segmentation may significantly affect the quality of an image understanding system [CHE, 06]. The most common features used in image segmentation include texture, shape, grey level intensity and color. The creation of the precise data space is a common problem in correlation with segmentation/classification of objects present in the images. In order to construct realistic classifiers, the features that represent the physical process must be searched. It is realistic that different transforms are used to extract the desired information from remote-sensing images or biomedical images [MEH, 05].

Segmentation evaluation techniques can be generally categorized as supervised and unsupervised. The supervised 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 [DAR, 03]. Unsupervised learning is normally used to locate patterns in the input data. No information is given to the system, which finds the patterns as to the correctness or incorrectness of the patterns. The patterns it finds may therefore be arbitrary or they may actually be representative of some real underlying process which caused them to appear gives for details on unsupervised classification.

Clustering is a process 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. Then the segmented image features are extracted based on the specific requirements of ground features classification [DEJ, 04]. The color homogeneity is based on the standard deviation of the spectral colors, while the shape homogeneity is based on the compactness and smoothness of shape.

5.3.1. Region-based Segmentation methods

Region-based segmentation methods are mainly based on the hypothesis that the neighboring pixels are compared with the pixels, within the same region which have similar value. If a similarity condition is satisfied, the pixel can be set, and clustered as one or more of its neighbors. The selection of the similarity condition is significant and the results are influenced by noise in all occasions.

In this research work, seeded region growing segmentation is carried out using mean-shift algorithm and by using k-means clustering to segment the cluster for six colored regions of the enhanced satellite images.
5.3.2. **Seeded Region Growing Segmentation**

The seeded region growing segmentation algorithm is one of the simplest region-based segmentation methods. It performs segmentation in an image which examines the neighboring pixels, a set of points known as seed points and determines whether the pixels could be classified to the cluster of seed point or not [ADA, 94].

The seeded region growing algorithm is shown below:

*Step-1:* Start with a number of seed points which have been clustered into \( n \) clusters, called \( C_1, C_2, \ldots, C_n \), and the positions of initial seed points is set as \( p_1, p_2, \ldots, p_n \).

*Step-2:* Compute the difference between a pixel value of the initial seed point \( p_i \) and its neighboring points. If the difference is smaller than the threshold, then the neighboring point could be classified into \( C_i \), where \( i = 1, 2, \ldots, n \).

*Step-3:* Recompute the boundary of \( C_i \) and set those boundary points as new seed points \( p_i(s) \). In addition, the mean pixel values of \( C_i \) have to be recomputed.

*Step-4:* Repeat step 2 and 3 until all pixels in image have been allocated to a suitable cluster.

The threshold is assigned by the image analyst and it is usually based on intensity, gray level or color values. The regions are chosen to be, as uniform as possible. The segmentation regions have high color similarity and no disconnected problem. Thresholding approaches segment scalar images by creating a binary partitioning of the image intensities. Figure 5.1(a) shows the histogram of a scalar image that possesses three apparent classes corresponding to three different intensity values. A thresholding method attempts to determine an intensity value, called the *threshold*, which separates the desired classes. The segmentation is then achieved by grouping all pixels with intensity greater than the threshold into one class, and all other pixels into another class. Two potential thresholds are shown in Figure 5.1(a) at the valleys of the histogram. Determination of more than one threshold value is a process called multithresholding [SHO, 88]. Figure 5.2 illustrates the seeded region-growing process.
5.3.3. Mean Shift algorithm

The mean shift algorithm is a robust feature-space analysis approach [COM, 02] which can be applied to discontinuity preserving smoothing and image segmentation problems. It can significantly reduce the number of basic image entities, and due to the good discontinuity preserving filtering characteristic, the significant features of the overall image are retained. Because of this property it is particularly important in the partitioning of natural images, in which only several distinct regions are used. In representing different scenes such as land, sea, lake, sky, person, sand beach and animal whereas other information within a region is often less important and can be neglected. However, it is difficult to partition a natural image into significant regions to represent distinct scenes, depending only on the mean shift segmentation algorithm. The main reason is that the mean shift algorithm is an unsupervised clustering-based segmentation method where the number and the shape of the data cluster are unknown a priori.
The mean shift algorithm classifies the image based on density estimation. It effectively analyzes feature space to cluster them and can provide consistent solutions for many vision tasks. The mean shift procedure is described as below:

Given $n$ data points $x_i$, $i=1,..., n$ in the $d$-dimensional space $R^d$ and set one bandwidth parameter $h > 0$. The mean shift is

$$m_{h,k}(x) = \frac{\sum_{i=1}^{n} x_i^k \left( \frac{|x-x_i|}{h} \right)}{\sum_{i=1}^{n} k \left( \frac{|x-x_i|}{h} \right)} - x,$$  \hspace{1cm} (5.1)

where kernel $k(p)$ is

$$k(p) = \begin{cases} 
1 & x \leq 1 \\
0 & x > 1,
\end{cases}$$  \hspace{1cm} (5.2)

when $m_{h,k}(x)$ is smaller than a threshold, that means convergence then it can be stopped to calculate mean shift. But if $m_{h,k}(x)$ is bigger than threshold, it should set $m_{h,k}(x)$’s first term be the new mean and repeat computing $m_{h,k}(x)$ until convergence.

### 5.3.4. Color Image Segmentation based on Mean Shift

Color images carry more information than grayscale images [CHE, 01]. In many pattern recognition and computer vision related applications, the color image information can be used to enhance the image analysis process and improve segmentation results compared to grayscale based approaches.

Image segmentation algorithms are classified into three major categories namely: feature-space-based clustering, spatial segmentation and graph-based approaches. Feature-space-based clustering approaches [JAC, 00], [JAI, 97] capture the entire global characteristics of the image through the selection and evaluation of image features, usually based on color or texture. The spatial segmentation method is also referred to as region-based when it is based on region entities. The watershed algorithm [VIN, 91] is
the widely used technique for this purpose. Graph-based approaches can be considered as image perceptual grouping. Organization methods based on the fusion, the feature and spatial information has the key factors such as similarity, proximity and continuation. This approach is based on the formation of a weighted graph, where each vertex corresponds to an image pixel or a region. The weight of each edge connecting two pixels or two regions represents the likelihood that they belong to the same segment. This depends on the color and texture features, as well as spatial characteristics of the corresponding pixels or regions. Figure 5.3 illustrates the segmentation of objects in various images using mean shift algorithm.

5.3.5. Edge based Image Segmentation using Watershed transformation

Edge-based image segmentation normally indicates the segmentation method based on the edges in an image. The edge detection methods applied before segmentation are gradient operators [PRA, 07] and Hilbert transform [PEI, 03] in addition to the watershed transformation to preserve the edges on the images during segmentation.

Watershed transformation algorithm was introduced by Vincent and Soille in 1991. It is a segmentation algorithm based on the inundation process of the image gradient which is observed as a relief. It aims at finding the peaks in the image gradient called watersheds and identifying them as the image contours. Due to its flexibility and rapidity, this algorithm is used in several applications. The two properties of watershed transformation in image segmentation are the continuous boundaries and over-segmentation. Over-segmentation is the major drawback which can be reduced by making use of makers to solve this problem.

Watershed transformation is applied with numerical tests for the segmentation problems using mathematical morphology tools. This approach is used in this research work to preserve the edge features during segmentation process. The following section explains briefly about the basic notations and the morphological operators namely the dilation and erosion that are used in the watershed transformation.
Figure 5.3 Segmentation of images obtained using mean-shift algorithm


The main objective of watershed segmentation algorithm is to find the “watershed lines” in an image in order to separate the different regions. To visualize the pixel values of an image is a 3D topographic chart, where \(x\) and \(y\) denote the coordinate of plane, and \(z\) denotes the pixel value. The algorithm starts to pour water in the topographic chart from the lowest basin to the highest peak. In the process, one may detect some peaks disjoined the catchment basins, called as “dam”. Figure 5.4 illustrates the schematic overview of the flooding algorithm for the watershed method and Figure 5.5 illustrates inverted schematic overview to emphasize the flooding.

Let \(u(x,y)\) with \((x,y) \in \mathbb{R}^2\), be a scalar function describing an image \(I\). The morphological gradient of \(I\) is defined in [BEU, 93].

\[
\delta_D u = (u \oplus D) - (u \ominus D) \tag{5.3}
\]

where \((u \oplus D)\) and \((u \ominus D)\) are respectively the elementary dilation and erosion of \(u\) by the structuring element \(D\).

The morphological Laplacian is given by

\[
\Delta_D u = (u \oplus D) - 2u + (u \ominus D) \tag{5.4}
\]
Here, the morphological Laplacian allows distinguishing influence zones of minima and suprema: regions with $\Delta_D u < 0$ are considered as influence zones of suprema, while regions with $\Delta_D u > 0$ are influence zones of minima. Then $\Delta_D u = 0$ allows interpreting edge locations, will represent an essential property for the construction of morphological filters. The basic idea is to apply either dilation or erosion to the image $I$, depending on whether the pixel is located within the influence zone of a minimum or a maximum. Dilation adds pixels to the boundaries of objects in an image, while erosion removes pixels on object boundaries. The number of pixels added or removed from the objects in an image depends on the size and shape of the structuring element used to process the image.
The catchment basin $C(M)$ associated to a minimum $M$ is the set of pixels $p$ of $\Omega$ such that a water drop falling at $p$ flows down along the relief, following a certain descending path, and eventually reaches $M$. The catchment basins of an image $I$ correspond then to the influence zones of its minima, and the watershed will be defined by the lines that separate adjacent catchment basins.

Several algorithms have been proposed for the computation of watersheds and the most commonly used, are based on an immersion process analogy. According to [VIN, 91], the immersion process is considered as follows. $h_{\text{min}}$ and $h_{\text{max}}$ are the smallest and the largest values taken by $u$. Let $T_h = \{p \in \Omega, u(p) \leq h\}$ be the threshold set of $u$ at level $h$. The recursions with the gray level $h$ increasing from $h_{\text{min}}$ to $h_{\text{max}}$, in which the basins are associated with the minimum of $u$ are successively expanded. Now consider $X_h$ the union of the set of basins computed at level $h$. A connected component of the threshold set $T_{h+1}$ at level $h+1$ can be either a new minimum, or an extension of a basin in $X_h$. Finally, by denoting by $\min_h$ the union of all regional minima at level $h$, the following recursion which defines the watershed by immersion

$$
\begin{align*}
X_{h_{\text{min}}} &= T_{h_{\text{min}}}, \\
\forall h \in [h_{\text{min}}, h_{\text{max}} - 1],
X_{h+1} &= \min_{h+1} \cup IZ_{T_{h+1}}(X_h),
IZ_{T_{h+1}} &= \bigcup_{i=1}^{k} iz_{T_{h+1}}(X_h),
IZ_{T_{h+1}} &= \bigcup_{i=1}^{k} iz_{T_{h+1}}(X_h),
\end{align*}
$$

(5.5)

where $k$ is the number of minima of $I$,

and $\bigcup_{i=1}^{k} iz_{T_{h+1}}(X_h)$ is defined by

$$
iz_{\Omega}(Y_i) = \{z \in \Omega, \ \forall k \neq i, d_{\Omega}(z, Y_i) \leq d_{\Omega}(z, Y_k)\}
$$

The set of the catchment basins of a gray level image $I$ is equal to the set $X_{h_{\text{max}}}$. At the end of this process, the watershed of the image $I$ is the complement of $X_{h_{\text{max}}}$ in $\Omega$. The main problem of this method is that the images can often be noisy, which implies that have a lot of local minima and this leads to an over-segmentation. In this research work, a novel method is introduced which decreases the over-segmentation by means of
watershed transformation is considered. The method is based on the topological gradient approach which has an interesting property to give more weight to the main edges. Obviously, it provides a more global analysis of the image than the Euclidean gradient or the morphological gradient. The results show that the images are less sensitive to noise and thus preserve the edge features of the images.

5.4. MORPHOLOGICAL OPERATIONS FOR EDGE PRESERVATION

Morphology is the study of the shape and form of objects. Morphological operations apply a structuring element to an input image, creating an output image of the same size. In a morphological operation, the value of each pixel in the output image is based on a comparison of the corresponding pixel in the input image with its neighbors. By choosing the size and shape of the neighborhood, the image is constructed to perform morphological operations that are sensitive to specific shapes in the input image.

Morphological image analysis can be used to perform the following:

- Object extraction
- Image filtering operations, such as removal of small objects or noise from an image
- Image segmentation operations, such as separating connected objects
- Measurement operations, such as texture analysis and shape description

In image processing, the morphological operations performed are: erosion, dilation, opening and closing. Combinations of these blocks are used to perform common image processing tasks and morphological image analysis, like contrast enhancement, noise removal, thinning, skeletonization, filling, image filtering, image segmentation and measurement operations.

In this proposed work, dilation and erosion morphological operations are considered and are amalgamated with the watershed transformation process used for edge preserving techniques. Dilation adds pixels to the boundaries of objects in an image, while erosion
removes pixels on object boundaries. The number of pixels added or removed from the objects in an image depends on the size and shape of the structuring element used to process the image. The state of any given pixel in the output image is determined by applying a rule to the corresponding pixel and its neighbors in the input image. The morphological operations of dilation and erosion that are performed on pixels of the images can be summarized as follows:

Dilation operation will find the local maxima in binary or intensity images. Here the value of the output pixel is the maximum value of all the pixels in the input pixel's neighborhood. In a binary image, if any of the pixels is set to the value 1, the output pixel is set to 1. Erosion operation will find local minima in binary or intensity images. Here the value of the output pixel is the minimum value of all the pixels in the input pixel's neighborhood. In a binary image, if any of the pixels is set to 0, the output pixel is set to 0. Figure 5.6 illustrates the segmentation technique with watershed transformation and morphological operations.

<table>
<thead>
<tr>
<th>Original Image</th>
<th>6 color segmented image</th>
<th>Watershed transformed image</th>
</tr>
</thead>
</table>

Figure 5.6 Proposed segmentation technique with watershed transformation using morphological operators

5.5. IMAGE CLUSTERING

Image clustering is a method based on region-based image segmentation, and it is widely used in image processing and pattern recognition. Use the centroids or prototypes to
present the great numbers of cluster to accomplish the two goals namely, reducing the computational time consumed and providing a better condition to reduce it.

In image segmentation, clustering is a process whereby an image is considered as a group of clusters, which are collections of same color pixels that “belong together”. Pixels may belong together because they have the same color and/or they have the same texture and/or they are nearby, etc., In general, clustering can be classified into two types namely, hierarchical clustering and partitional clustering. In the hierarchical clustering, change the numbers of cluster during the process. However, in the partitional clustering, decide the numbers of cluster before processing. Except for these two classes, mean shift algorithm is part of image clustering, and its concept is based on density estimation, the color nearness and proximity.

5.5.1. Hierarchical clustering

The hierarchical clustering algorithms are categorized into two types. They are:

- Divisive clustering
- Agglomerative clustering

In divisive clustering, the entire image set is regarded as a cluster, and then clusters are recursively split to yield a good clustering. The pseudo code for the divisive algorithm is shown below:

Begin

Step 1: Construct a single cluster containing all points

Step 2: Until the clustering is satisfactory

Step 3: Split the cluster that yields the two components with the largest inter-cluster distance

End

In agglomerative clustering, each color pixel item is regarded as a cluster and clusters are recursively merged to yield a good clustering. The pseudo code for the agglomerative algorithm is shown below:
Begin

Step 1: Make each point a separate cluster
Step 2: Until the clustering is satisfactory
Step 3: Merge the two clusters with the smallest inter-cluster distance

End

5.5.2. Partitional clustering

In the partitional clustering, one has to decide the number of clusters before processing. The K-means algorithm is most well-known in the partitional clustering and is discussed below.

K-means algorithm:

Step 1: Place K points into the space represented by the objects that are being clustered. These points represent initial group centroids.
Step 2: Assign each object to the group that has the closest centroid.
Step 3: When all objects have been assigned, recalculate the positions of the K centroids.
Step 4: Repeat Steps 2 and 3 until the centroids no longer move. This produces a separation of the objects into groups from which the metric to be minimized can be calculated.

5.6. SATELLITE IMAGERY CLASSIFICATION USING K-MEANS ALGORITHM

Segmentation and classification of high resolution satellite imagery is a challenging problem to carry out the task on a pixel-by-pixel basis. The fine spatial resolution involves that each object is an aggregation of a number of pixels in close spatial nearness, and precise classification. K-means clustering algorithm is a better method of classifying high resolution satellite imagery. The extracted regions are classified using a minimum distance decision rule.
Clustering is the process by which discrete objects with similar characteristics can be assigned to groups. Clustering is used to group the similar objects together like a class, review results, or satellite image data, among others. Clustering algorithm has been used as a tool to analyze varieties of data. According to [JAI, 99], this concept has been researched by many clustering practitioners, indicating how useful it is in image analysis. It is the unsupervised classification of patterns derived from observations, object items and or feature vectors into groups or clusters. For clustering the image, the following components of a typical clustering task have been considered, which include the pattern representation, definition of pattern nearness measure appropriate to certain data domain and clustering or grouping as shown in figure 5.7.

![Figure 5.7 Clustering stages](image)

The separation of the objects into groups from which the metric to be minimized can be calculated by the objective function of a squared error function.

The objective function is

\[
J = \sum_{j=1}^{k} \sum_{i=1}^{n} ||x_i^{(j)} - c_j||^2
\]

(5.6)

where \( ||x_i^{(j)} - c_j||^2 \) is the selected distance measure between a data point \( x_i^{(j)} \) and the cluster centre \( c_j \) which is an indicator of the distance of the \( n \) data points from their respective cluster centres.
5.7. COLOR-BASED SEGMENTATION USING K-MEANS CLUSTERING

The algorithm of color segmentation belongs to the general class of region growing type of segmentation scheme. If a color profile is given in form of its three component profiles: red, green and blue, then the two markers $x$ and $y$ will be defined labels. Then choose a similarity measure between a point and its neighboring marked region. In this case, the color difference between the point and its neighbor already in the marker which is simply a trivial color difference. If $(rx, gx, bx)$ and $(ry, gy, by)$ are the values of two colored pixels, $x$ and $y$, then the color difference is:

$$
M a x ( | r x - r y | , | g x - g y | , | b x - b y | )
$$

(5.7)

But this is a coarse color measure in reality. In the case of satellite imagery a CIE L* a* b* color scale has been used. This is a uniform scale color and a standard for colors to be compared with [HUN, 08]. Here L* axis represents the intensity variation from top to bottom, 100 to 0 values, which represents a perfect intensity diffuser; a* the color variation along red-green axis, positive a* is red and negative a* is green; while b* represents the color variation along blue-yellow axis of the scale with positive b* yellow and negative b* blue. In this research work, the environmental features are the objects of interest from the imagery. K-means clustering treats each object as having a location in space. It finds clusters such that objects within each cluster are as close to each other, from the objects in other clusters.

5.8. PROPOSED AMALGAMATION OF MEAN SHIFT ALGORITHM USING WATERSHED TRANSFORM AND MORPHOLOGICAL OPERATIONS (AMWM)

In this research work, a novel amalgamation algorithm is applied on the enhanced satellite image for segmenting and clustering it into six different color regions. This algorithm is called as “Amalgamation of Mean shift algorithm (k-means), Watershed transform and Morphological operations (AMWM)”. 

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This algorithm is a mixture of the mean shift algorithm (k-means), which segments the closed region boundaries and gives solid results, by automatically separating different clusters into six color regions. Watershed transform is a segmentation method is applied on the color regions, which classifies pixels according to their spatial proximity (nearness), the gradient of their gray levels and the homogeneity of their textures. Finally morphological operations like dilation and erosion are applied on the image to separate connected objects. This works removes the drawbacks such as (i) sensitivity to noise and (ii) over and under segmentation. The proposed segmentation and clustering process is explained in the following section.

5.8.1. Proposed Segmentation process

The enhanced image is segmented using a segmentation algorithm that combines watershed algorithm with mean-shift clustering algorithm and is explained in this section. Watershed Transform (WT), which through the flooding of the valleys, is capable of recognizing similar topographical areas, surrounded by mountain ridges. The WT is a segmentation method based on regions, which classifies pixels according to their spatial proximity, the gradient of their gray levels and the homogeneity of their textures [GON, 09]. Watershed segmentation is a predominant segmentation scheme with several advantages. It ensures the closed region boundaries and gives solid results. It is a way of automatically separating or cutting apart particles that touch. The watershed algorithm uses concepts from mathematical morphology to partition images into homogeneous regions. Careful analysis of this system identified two major drawbacks, (i) sensitivity to noise and (ii) over and under segmentation. The first problem can be solved by using the preprocessing step which removes noise and at the same time, preserve the features that represent the image boundaries. The over segmentation problem can be solved by using an appropriate clustering algorithm to group similar pixel values together.

Normally to handle the over-segmentation problem of watershed algorithm, the over-segmented regions will be clustered using k-means algorithm [GON, 09]. The result while reducing the over-segmentation problem requires the correct selection of ‘k’ in the
k-means algorithm. In this proposed research work, this problem is solved by using a non-parametric clustering algorithm, namely, mean-shift clustering algorithm [SHA, 12]. The proposed algorithm is shown in Figure 5.8. The algorithm starts by applying the traditional watershed transformation that uses the regional minima as starting markers. This step results with an image where each pixel is identified to belong to regional minima.

![Proposed clustering algorithm](image)

**Figure 5.8 Proposed clustering algorithm**

### 5.8.2. Proposed Clustering process

The second step analyzes the texture of the labeled image and creates a feature vector based on the mean and standard deviation of each region. The mean-shift clustering algorithm is applied to group regions with similar features, thus reducing the number of regions. These regions are now used as optimal markers and the morphological operations were applied to obtain the internal markers. Open and close operators were used to join adjacent regions corresponding to adjacent regions belonging to same objects. The results
are then used as internal markers during final wavelet transform. The erosion operator was then applied to compliment the internal markers and to obtain the external or background markers. The obtained internal and external markers are then used to obtain the final segmented image. The mean shift clustering algorithm is used to merge regions.

The mean shift estimate of gradient of a density function and the associated iterative procedures of mode seeking has been developed by Fukunaga and Hostetler [FUK, 75]. The property of data compaction of the mean shift has been exploited in image segmentation. Based on the idea of iteratively shifting a fixed size window to the average of the data points was taken. The mean shift procedure can be obtained by successive compute the mean shift vector $M_h(x)$, and translate the window $S_h(x)$ by $M_h(x)$.

$$M_h(x) = \frac{1}{n} \sum_{x_i \in S_h(x)} x - x_i$$

(5.8)

The mean shift vector always points towards the direction of the maximum increase in the density $f(x)$, so it can define a path leading to a local density maximum.

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

(5.9)

Let $\{x_i\}_{i=1..n}$ be an arbitrary set of $n$ points in the $d$-dimensional Euclidean space $\mathbb{R}^d$. $f(x)$ is the multivariate kernel density estimate with the kernel $K(x)$ and the window $S_h(x)$ radius $h$.

The mean shift filtering procedure is:

For each $j = 1,...,n$,

Initialize $k = 1$ and $y_k = x_j$

Compute

$$y_{k+1} = \frac{1}{n_k} \sum_{x_i \in S_h(y_k)} x_i, k \leftarrow k + 1$$

(5.10)
Assign \( Z_j = (x'_j, y'_{\text{conv}}) \)

Let \( \{z_j\}_{j=1..n} \) be the \( d \)-dimensional original and filtered image in the spatial-range domain. The \( s \) and \( r \) denote the spatial and range parts of the vectors, respectively. The last assignment specifies that the filtered data at the spatial location of \( x_j \) will have the range components of the points of convergence \( y_{\text{conv}} \).

5.9. RESULTS AND DISCUSSIONS

The outcome of the proposed mean shift color segmentation with k means clustering technique along with water transformation and morphological operations is a parametric approach of image classification. However the satellite imagery has high inter-class and intra-class similarity, the classification was successful. Table 5.2 shows the six different types of objects that have been segmented from the satellite images. Six different colors are selected based on the nature of the imagery for the partition and a distance metric to quantify how close two objects are to each other has been determined. This distance is known to be a measure of “closeness”. For every object in input imagery, k-means returns an index equivalent to a cluster. Label every pixel in the image with its cluster index. The cluster center output from k-means is determined.

The experiment has been conducted for a number of satellite images. Figure 5.10(a) is a sample of an original satellite image taken for this experimental consideration. The segmented image shows the six types of objects namely; water is shown in violet, buildings in cream, trees in green, rocks in red, active agricultural land in yellow and dry land in orange. The features with their general boundaries have been clearly classified with their segmentation time is as shown in figure 5.10(b) to figure 5.10(f). The result is reasonably outstanding, and the only thing to bear in mind is the correct number of clusters that the imagery should contain. Figure 5.11 shows the six types of clustered images of each object that has been segmented. Table 5.1 shows the segmentation times (in seconds) for the existing mean shift (k-means clustering) method and the proposed AMWM method. While comparing the segmentation time the proposed method segments
and clusters the given input satellite images in a faster manner. The segmentation time results can be graphically viewed in figure 5.9.

Table 5.1 Comparison of Segmentation time (sec)

<table>
<thead>
<tr>
<th>Images</th>
<th>Mean shift - k-means clustering (seconds)</th>
<th>Proposed (AMWM) method</th>
</tr>
</thead>
<tbody>
<tr>
<td>Image1</td>
<td>110</td>
<td>97</td>
</tr>
<tr>
<td>Image2</td>
<td>118</td>
<td>102</td>
</tr>
<tr>
<td>Image3</td>
<td>123</td>
<td>103</td>
</tr>
<tr>
<td>Image4</td>
<td>113</td>
<td>99</td>
</tr>
</tbody>
</table>

![Comparison of Segmentation Time](image)

**Figure 5.9  Comparison of segmentation time**

Table 5.2 Clustered color representing the different types of objects present in the satellite images

<table>
<thead>
<tr>
<th>Water</th>
<th>Buildings</th>
<th>Trees</th>
<th>Rocks</th>
<th>Active agriculture</th>
<th>Dry lands</th>
</tr>
</thead>
</table>

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Figure 5.10 Segmentation with six color regions - Results of the proposed (AMWM) method
Objects in cluster-1

(a) – Class type: Water

Objects in cluster-2

(b) – Class type: Buildings

Objects in cluster-3

(c) – Class type: Trees

Objects in cluster-4

(d) – Class type: Rocks

Objects in cluster-5

(e) – Class type: Active agriculture

Objects in cluster-6

(f) – Class type: Dry lands

Water | Buildings | Trees | Rocks | Active agriculture | Dry lands
---|---|---|---|---|---

Figure 5.11 Six clustered regions extracted from the segmented image
5.10. CONCLUSION

The proposed AMWM algorithm has been tested with a number of images. The proposed method proved that the segmentation and clustering of satellite images has shown good results when compared with the existing k-means method. While comparing the segmentation time, the proposed method took less time for segmenting and clustering against the k-means method, and hence it is proved that the proposed method is better than the existing k-means method. This works removes the drawbacks such as (i) sensitivity to noise and (ii) over-segmentation.

Although many literatures claimed that one could accurately map land cover from satellite imagery data, in practice, it is an extremely difficult task. There are many instances in which land cover classification developed successfully at one site, fails in another.