Chapter 5
Region Detection and Change Map Formulation for Change Detection

5.1 INTRODUCTION

The important processes of change detection in remote sensed image are the determination of the region that has undergone changes and the change map formulation that reflects the changes happened between the timestamps. The process of region detection generally focuses on distinguishing changed region from unchanged region. Usually, the region detection process for any image processing applications is approached using supervised, unsupervised and semi-supervised approach to detect the region of interest. Especially for remote sensed images, this process helps in the generation of distinct clusters within the spectral space of an image to distinguish the different region as required for specific application. In the case of determining the changes, these methods provide meaningful outcome for interpretation.

Followed by the region detection, another important sub process that creates challenges in change detection is the change map formulation.

This chapter elaborates the process of region detection and change map formulation adapted to determine the changes in the multi-temporal multispectral Landsat images.

5.2 ANALYSIS OF VARIOUS REGION DETECTION METHODS

Region detection process is generally carried out to extract meaningful spatial coverage ranging from pixel to objects. These region forms the building blocks of many image application. In specific, in the remote sensed images, detecting region is important to provide worthy space cue for critical interpretations. Commonly, two approaches are widely followed for the region detection to detect changes in remote sensed images. One is supervised mode and the other is the unsupervised mode. In general, the supervised approaches deals with the identification known through a
combination of spectral characteristics of an image or region where, each pixel both within and outside the training sets are evaluated and assigned to a class of which it has maximum likelihood of being a member. The method could not succeed very much as the evaluation depends upon more samples and ground truth images for training to meet the accuracy. Due to the scarcity of the ground truth data the method could not be proceeded effectively. In addition as the generation of a training set is difficult and expensive task, the use of supervised methods is discouraged in many applications. Therefore, the pattern got shifted to unsupervised approaches of change detection. The unsupervised approaches have become compulsory in most of the remote sensed applications as challenges are high in supervised mode. The mode does not require any target attribute. Especially, in the case of remote sensed images, this method requires no extensive prior knowledge and has limited control over classes and identities. Ultimately, this method aims at generating distinct clusters within the spectral space of an image. The advantage of this method is to take maximum benefit of spectral variability in an image. Considering the advantage of unsupervised mode a number of unsupervised modes is tried for change detection and the same is elaborated in the subsequent sections.

5.2.1 K-MEANS CLUSTERING

K-means is one of the simplest unsupervised learning methods to classify a given data set through a certain number of clusters. The k-means partitioning of K clusters depends on the initial seed point to represent a well suited cluster (Celik 2009). Each observation is assigned to the nearest seed to form a set of temporary clusters. The seeds are then replaced by the cluster means, the points are reassigned, and the process continues until no further changes occur in the clusters. Thus, the method focuses on the minimization of the objective function as stated below,

\[ J = \sum_{j=1}^{k} \sum_{i=1}^{n} \left\| x_{i}(j) - c_{j} \right\|^2 \]  

(5.1)

where \( \left\| x_{i}(j) - c_{j} \right\|^2 \) is a chosen distance measure between a data point \( x_{i}(j) \) and the cluster centre \( c_{j} \), is an indicator of the distance of the ‘n’ data points from their respective cluster centres.

The steps followed for the K-Means Clustering process is represented as,
K means Clustering

**Input:** \( K \)=Number of clusters

Fused Image \( F \), dataset of \( N \) points

**Output:** A set of \( K \) clusters

Initialize \( K \) and cluster centre \( C \)

**Repeat**

For each point \( P \) in \( F \) do,

Find the nearest centre and assign \( P \) to the corresponding cluster as

\[
J = \| P - C \|^2
\]

End for

Update clusters by calculating new centres using mean of the members

Until no updation in cluster center.

Return cluster output.

5.2.2 ADAPTIVE K-MEANS CLUSTERING

According to K-means clustering, data is partitioned in to \( K \)–clusters and is completely depends on the initial seed point identification, and the predefined number of clusters (Bhagwati and Singha 2010). The method is simple, yet suffers unclear strategy for choosing initial seed point. Hence, the idea of clustering got extended to adaptive K means method. The method partition the given data without having any dependency of the initial seed point to represent the clusters. The method identifies \( K \) clusters by reordering the clusters to reflect well the partition. The process speed up significantly than the \( K \)–means as the seed point of generated clusters are not recomputed for each new assignment.

The steps of Adaptive K-means are elaborated as follows:

**Input** \( K \)=Number of clusters

Fused Image \( F \), dataset of \( N \) points

**Output:** A set of \( K \) clusters

**Begin**

Initialize \( K \) and Cluster centre \( C \)

**Repeat**
Find distance between the seed point and the point in the dataset of the image using

Euclidean distance. \( (x, y) = D(y, x) = \sqrt{\sum_{i=1}^{n}(y_i - x_i)^2} \)

Update the mean
Store center of the cluster and update the seed.
Check maximum number of clusters
Find out Difference between two consecutive centers and find the minimum distance.
Discard the cluster centers which are less than distance.
Make a clustered image using these centers.
Until convergence.

End

5.2.3 FUZZY C-MEANS CLUSTERING

Fuzzy c-means (FCM) is a method of clustering that allows a data to belong to two or more clusters. The method assigns membership to each data point associated with each cluster centre based on the distance between the cluster and the data point (Ghosh et al., 2010). The nearer the data to the cluster center the membership is more towards the cluster center. Like K-Means, FCM also minimizes the sum of squared error (SSE). The sum of membership of each data should converge to one and for each iteration, the membership and the cluster seed are updated. Though the method appears to converge faster, the processing time is lengthy and is sensitive to the initial assignment.

The procedure adopted for performing Fuzzy C – means is:

Input \( K= \) Number of clusters
Fused Image \( F \), dataset of \( N \) points

Output: A set of \( K \) clusters

Begin

1. Let \( X_i \) be the vector values of the fused image \( F \)
2. Initialize random membership function \( U^k = u_{ij} \) and cluster centroid \( C_j \)
3. Compute the fuzzy centroid \( F^k_j \) for \( j = 1, 2, ..., k \) where \( k \) is the number of clusters

End
\[ F_c = \frac{\sum_{i=1}^{N} (u_{ij})^m x_i}{\sum_{i=1}^{N} (u_{ij})^m} \]

where \( m \) is the fuzzy parameter and \( N \) is the data points

4. Update the fuzzy membership \( U^k = u_{ij} \) using,

\[ u_{ij} = \frac{1}{\sum_{j=1}^{N} \frac{1}{\|X_i - C_j\|^{(m-1)}}} \]

5. If \( \|U^k - U^{k-1}\| < \varepsilon \), then stop else return to step 2.

End

Ultimately, these methods have a disadvantage of having maximum separable clusters which may not match important classes of user’s perception. Especially, for change detection in the remote sensed image, these irrelevancy on perceptional view may degrade the accuracy of changes happened between longer timestamps. Therefore, in applications which require guided region detection for change determination, getting a priori knowledge of changes may be advantageous. Hence, the clustering process is extended to include the change knowledge in terms of constraints. One of the widely used constrained clustering is the constrained k-means method. However, this method has been adopted usually to cluster the dataset having raw data rather than images. Hence, a trial is made towards applying the constrained semi-supervised clustering for change detection in remote sensed images.

In addition, these methods follow mostly unsupervised approach that may not effectively provide the change details. Hence, the advantageous features of supervised and unsupervised methodology may be utilized to earn maximum benefits. Therefore, a combined approach called semi-supervised mode is recommended. This type of clustering uses a small amount of labelled data to aid and bias the clustering of unlabelled data which would be providing effective clusters that would reveal changes in a better way.

5.2.4 CONSTRAINED CLUSTERING

The Constrained Clustering is a semi-supervised clustering method, which is typically represented as set of must link, cannot link or both with data. Any two instances that
are associated by must link constraints (MLC) states that these instances are belonging to same cluster. While cannot link constraints (CLC) restricts the instances to be in the same cluster. Hence, by using the constrained clustering method, a region map is created. The region detection process adapted to find out the changes and to create the region map for easy detection process is provided as:

The procedure initializes two different clusters, one for the MLC satisfied regions while other for CLC based regions. Considering each pixel of the fused image, the closeness to MLC cluster and CLC cluster is determined. By clustering under these two categories, the region is detected. The procedure adopted for the constrained clustering is as follows:

**Input:** $K=$Number of clusters

*Fused Image F, dataset of N points*

**Output:** A set of K clusters

**Initialize:** Cluster centers, Must Link Constraints, Cannot Link Constraints

**Begin**

For each point $F_{di}$ in $F_d$

1. Assign it to the closest cluster $C_i$ such that violate constraints is false.

2. If no such cluster exists, raise exception

For each cluster $C_k$,

3. Update’s its center by averaging all of the points $F_{dj}$ that has been assigned to it.

4. Repeat steps 1 and 2 until convergence

**Violate-constraints**

For a cluster $C$ if the data points that must link to $F_{di}$ are not in $C$,

Must link constraint is violated.

For a cluster $C$ if the data points that cannot link to $F_{di}$ are in $C$,

Cannot link constraint is violated.

**End**

The detected region is expected to include the changes that have happened. Once the region of change is detected, it is essential to identify the unit of change and its associated class. This may be obtained by formulating region map to reflect the
changes happened at different time stamps. The change map highlights the region as changed and unchanged ones.

In order to expose the effectiveness of these unsupervised modes in detecting changes in multi-temporal multispectral Landsat images, initially, the standard clustering process such as K-Means, Adaptive K-Means and Fuzzy C-Means are attempted. Thus, the process of region detection using the popularly adopted methods is studied and evaluated to understand the scope for improvement.

The study helped to comprehend the different unsupervised clustering methods that are widely adopted for change detection process. Though these methods responded well in lieu with the manual method, it yielded a considerable amount of unwanted clusters that do not match the user’s expectation. Hence, a better solution is aimed through an improvement in the process. The improvisation is envisioned through a semi supervised approach to minimize the irrelevant clusters that are usually formed in unsupervised methods. The proposed method gives elevation to the design of two approaches using constrained clustering such as,

- Enhanced Constrained Clustering Method (ECKM)
- Adapted Sparse Constrained Clustering Method (ASCC)

5.3 ENHANCED CONSTRAINED CLUSTERING METHOD (ECKM)

The Enhanced Constrained Clustering (ECKM) method is the combination of sparse fusion and constrained clustering approach. The ECKM approach is shown in the Fig. 5.1.

Fig. 5.1: ECKM Method for Change Detection in Remotely Sensed Images.
Two co-registered and radiometric corrected multi-temporal multispectral images, acquired over the same geographical area with two different timings T1 and T2 are considered. The two difference images are generated using ADM and CVA techniques.

The two difference images are applied for fusion using sparse representation where, the image patches are extracted to update the dictionary. The resulted fused images are further applied to region detection using Constrained Clustering. The method emphasized the unification of fusion with clustering to provide an improved result than the other supervised and unsupervised methods. The advantage of the unification process is to guide the change detection through semi supervised mode where, partial labelling is encouraged through the reference image that is created as ground truth image. As the label is included, the change detection convergence is achieved much faster than any other approach. Thus, a change formation map is constructed from the clustered image comprising of changed and unchanged pixels.

5.4 ADAPTED SPARSE FUSION CONSTRAINED CLUSTERING METHOD (ASCC)

The Adapted Sparse fusion Constrained Clustering Method (ASCC) is the combination of Enhanced Sparse Coding (EDSR) and Constrained Clustering approach. The ASCC approach is shown in the Fig. 5.2.

Fig. 5.2: Designed ASCC Approach for Change Detection in Remotely Sensed Images.
According to this approach, fusion process is carried out through enhanced sparse coding, where the dictionary creation and updation is performed using uniform image patches extracted from the difference images. Unlike the other methods, where image patches are extracted in different irregular sizes, this method approaches it with uniform image patches of size $\sqrt{64} \times \sqrt{64}$ that reduces the under sized as well over sized patches which might lead to degradation of fusion process. Due to the uniform size of image patches, the overhead involved in extending the size of dictionary in regular intervals of time is restricted. Also, the learning process from the dictionary is said be very much organized with the initialization of regularization parameter indicating global error rate dynamically. In addition, the fusion is performed based on the absolute maximum value of the sparse coefficients which reduces the misclassification rate and improves the prominence of pixels to ease the change detection process. In the other stated methods, the regularization parameter is assigned with fixed error rate due to which, there is a possibility to have decreased accuracy. Also, these methods encourage fusion mostly through either maximum of sparse coefficients or through mean of sparse coefficient which would provide moderate and uniform visibility.

Therefore, by making the regularization parameter as a dynamic one and fusing absolute maximum value of sparse coefficient, an improved accuracy with reduced error rate is accomplished.

5.5 CHANGE MAP FORMULATION

The task of change map formulation takes a key role in the change detection process. A decision function to determine change in the unit such as pixel, region, cluster and in object is notified through a binary change map. Thus two major clusters with cluster centers denoted as $\gamma_1$ and $\gamma_2$ are obtained to reflect change and no change respectively. By computing the distance between cluster center and pixel of fused image using equation 5.2, the binary change map is created.

$$BC_{m(x,y)} = \begin{cases} 
1, & \|F(x,y) - \gamma_1\| \leq \|F(x,y) - \gamma_2\| \\
0, & \text{otherwise} 
\end{cases} \quad (5.2)$$
The distance between the fused pixel and the cluster1 in the Euclidean space is measured. The resultant image contains zeros and ones representing changed and unchanged areas.

Thus, the region detection and change map formulation is carried out to determine the changes that have happened between two timestamp of multispectral Landsat Images.

Thus, the analysis towards the suitability of region detection methods pushed to a decision of choosing ASCC as a better methodology to perform change detection in the multi-temporal multispectral images. However, the solution obtained through these clustering is the minimization of the objective function, so that it is clear that it would reach only local maxima. In case of change detection in remote sensed images, this may not provide the required accuracy as the minor changes in the region may not be reflected. Hence, it is required to optimize the solution so that all the possible changes are reflected in the change map to make change detection effective. One of the feasible approaches to carry such process is applying the binary change map obtained as result of region detection for optimization so that the global maximum is achieved. Thus the process demands to use evolutionary approaches that lead to fulfil the objective of reaching global maxima. The popular methods that converges solution to global maxima is PSO.

5.6 PARTICLE SWARM OPTIMIZATION

PSO is a robust stochastic optimization technique that works based on the association and intelligence of swarms. It involves a number of agents (particles) that constitute a swarm, moving around in the search space, looking for the global best solution. In this case, each particle can communicate to each of the other particle and thereby a fully connected network is formulated. Of course, each particle is attracted to the best particle out of entire swarm. Hence, this kind of approach is well suited for discrete optimization. One of the areas where the discrete optimization takes a prime role in the remotely sensed images is the change detection process. Especially, in the case of detecting changes happened in a region between time stamps T1 and T2, it is required to determine the changes happened in the whole area in terms of discrete regions if present. Hence, an appropriate method is needed to find such changes which may be
considered to be the global best with respect to that region of interest. Since the change map formulated is in the binary format, the process is carried out using binary particle swarm optimization. The optimization of the change map obtained using binary particle swarm optimization is shown in Fig. 5.3.

![Fig. 5.3: Optimization of Change Map using BPSO](image)

5.6.1 BINARY PARTICLE SWARM OPTIMIZATION

BPSO is a variant of PSO that is designed to handle discrete optimization problem. According to this method, each particle is assumed to be present in binary format. It differs from PSO in updating the particle using current velocity than by combining velocity and current position as in PSO. Due to this, it is always noted that the search space is based on the current velocity only. Hence position is not an issue, yet the method updates the velocity towards the pbest and gbest. Considering the accelerating concept, the change detection is approached.

Initially, a binary change detection mask is obtained by using the Adapted Sparse Constrained Clustering (ASCC) method. The ASCC method would generate a change map with significant changes in the multi-temporal images. The post processing using the BPSO is expected to improve the convergence rate and speed up the error minimization in finding the final change detection mask. The method searches the optimal solution by considering the created initial solution. Thus the particle is assumed to move towards the gbest and once the specified convergence is met, it is assumed that the gbest is achieved.
Thus, the change map formulated after applying BPSO will have changes projected prominently to result in improved visual effect on the change map. The process followed is shown in Fig. 5.4.

![Flow Diagram for Binary PSO](image)

**Fig. 5.4: Flow Diagram for Binary PSO**

The procedure adopted in the case of optimizing the solution space of change detection process is delineated as follows:

*Input: Initial particle is the binary change map formulated using ASCC*

*Output: Final Change detected image*

Choose binary change map formulated using ASCC as the initial population
Generate other populations randomly

Initialize the populations with random positions and velocities

For each population

Evaluate the fitness value for each population as,

\[ F_i = \left[ (N_0 \times \sum_{\forall (i,j) \in S_0} ADM(i,j) - \text{mean}(S_0))^2 + (N_1 \times \sum_{\forall (i,j) \in S_1} ADM(i,j) - \text{mean}(S_1))^2 \right] / (M \times N) \]

Fitness function = minimize \( F_i \)

Compare the current position of the particle to the pbest position

If

Current position is better.
Set current position \( \rightarrow \) pbest
Else continue with the old pbest.

Choose the particle having best fitness value and set as gbest.

Update the state ‘sta’ and velocity ‘vel’ of each particle as,

\[ \text{vel} = v_i + a1 \times \text{rand1} \times (\text{pbest} - s_i) + a2 \times \text{rand2} \times (\text{gbest} - s_i) \]
\[ \text{sta} = s_i + \text{vel} \]

Continue

Until convergence

End

In the designed BPSO method \( N_0 \) and \( N_1 \) are the number of elements in the set \( S_0 \) and \( S_1 \) respectively. \( S_0 \) denotes the number of elements in the current mask representing 0 and \( S_1 \) denotes the number of elements in the current mask representing 1. The mean of sets \( S_1 \) and \( S_2 \) will be,

\[ \text{mean}(S_0) = \left( \frac{1}{N_0} \right) \times \sum_{\forall (i,j) \in S_0} ADM(i,j) \]  \hspace{1cm} (5.3)

\[ \text{mean}(S_1) = \left( \frac{1}{N_1} \right) \times \sum_{\forall (i,j) \in S_1} ADM(i,j) \]  \hspace{1cm} (5.4)
where, ADM is the difference image created using Absolute difference method. The updation of state and velocity is based on the random variables ‘rand1’, ‘rand2’ and learning factors ‘a1’ and ‘a2’ of local and global information.

5.7 METRICS FOR PERFORMANCE STUDY

For the quantitative assessment of the attempted existing and proposed techniques, the following metrics have been computed for each change map with respect to the reference map.

- $T_p$ – the number of changed pixels identified correctly.
- $T_n$ – the number of pixels correctly identified as unchanged.
- $F_n$ – the number of changed pixels wrongly identified as unchanged pixels.
- $F_p$ – the number of unchanged pixels identified as changed pixels.

The quantities given above are evaluated by a confusion matrix and various metrics can be obtained using the above derived quantities to assess the performance of the defined procedures.

The definition of the applied metrics is as follows:

1. Overall Error (OE):
   Overall error deals with the probability that a changed pixel is wrongly identified as unchanged pixels.
   \[
   OE = \frac{F_n}{F_n + T_p} \tag{5.5}
   \]

2. Commission Error (CE)
   Commission error deals with the probability that an unchanged pixel is wrongly identified as changed pixels.
   \[
   CE = \frac{F_p}{T_n + F_p} \tag{5.6}
   \]

3. Percentage Correct Classification (PCC)
   It identifies the overall accuracy of the proposed method by means of detecting the changed pixels as changed and unchanged pixels as unchanged.
PCC = \frac{(T_p + T_n)}{(T_p + T_n + F_p + F_n)} \quad (5.7)

4. Precision
Precision is referred to the fraction of changed pixels identified correctly.
\[
\text{Precision} = \frac{T_p}{T_p + F_p} \quad (5.8)
\]

5. Recall
Recall is referred to the fraction of pixels that are relevant for the changes and are successfully identified for change detection
\[
\text{Recall} = \frac{T_p}{T_p + F_n} \quad (5.9)
\]

6. F1 measure
F1 measure is a measure which combines precision and recall. It is a harmonic mean of the both.
\[
\text{F1 measure} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \quad (5.10)
\]

7. G measure
G measure is a geometric mean of precision and recall
\[
\text{G measure} = \sqrt[\text{precision} \times \text{recall}} \quad (5.11)
\]

8. MCC (Mathew’s correlation coefficient)
\[
\text{MCC} = \frac{T_p + T_n - F_p + F_n}{\sqrt{(T_p + F_p)(T_n + F_n)(T_p + F_n)(F_p + F_n)}} \quad (5.12)
\]

Thus the proposed methodology of applying the semi supervised approaches for effective change detection is comprehended and justified based on the results obtained as enclosed in Chapter 6.