CLASSIFICATION OF SYNTHETIC APERTURE RADAR IMAGES USING PARTICLE SWARM OPTIMIZATION TECHNIQUE

A THESIS SUBMITTED IN PARTIAL FULFILLMENT

OF THE REQUIREMENTS FOR THE DEGREE OF

Master of Technology

In

Electronic Systems and Communications

By

VEDAVRATH LAKIDE

Reg. No: 207EE111

Department of Electrical Engineering
National Institute of Technology
Rourkela-769008
(2007-2009)

CLASSIFICATION OF SYNTHETIC APERTURE RADAR IMAGES USING PARTICLE SWARM OPTIMIZATION TECHNIQUE

A THESIS SUBMITTED IN PARTIAL FULFILLMENT

OF THE REQUIREMENTS FOR THE DEGREE OF

Master of Technology

In

Electronic Systems and Communications

By

VEDAVRATH LAKIDE
Reg. No: 207EE111

Under the Guidance of

Prof. DIPTI PATRA

Department of Electrical Engineering
National Institute of Technology
Rourkela-769008
(2007-2009)

National Institute Of Technology
Rourkela

CERTIFICATE

This is to certify that the thesis entitled, **"Classification Of Synthetic Aperture Radar Images Using Particle Swarm Optimization Technique"** submitted by **Mr. VEDAVRATH LAKIDE** in partial fulfillment of the requirements for the award of Master of Technology Degree in **Electrical Engineering** with specialization in **"ELECTRONIC SYSTEMS AND COMMUNICATIONS"** at the National Institute of Technology, Rourkela is an authentic work carried out by him under my supervision and guidance.

To the best of my knowledge, the matter embodied in the thesis has not been submitted to any other University / Institute for the award of any Degree or Diploma.

Date:

Prof. Dipti Patra
Department of Electrical Engineering
National Institute of Technology
Rourkela-769008

ACKNOWLEDGEMENTS

This project is by far the most significant accomplishment in my life and it would be impossible without people who supported me and believed in me.

I would like to extend my gratitude and my sincere thanks to my honorable, esteemed supervisor **Prof. Dipti Patra,** Department of Electrical Engineering. She is not only a great lecturer with deep vision but also most importantly a kind person. I sincerely thank for her exemplary guidance and encouragement. Her trust and support inspired me in the most important moments of making right decisions and I am glad to work under her supervision.

I am very much thankful to our Head of the Department, **Prof. Bidyadhar Subudhi**, for providing us with best facilities in the department and his timely suggestions. I am very much thankful to **Prof. P. K. Nanda** for providing valuable suggestions during my thesis work and all my teachers **Prof. J. K. Satapathy, Prof. S. Das, Prof. P. K. Sahu, Prof. K. R. Subhashini** and **Prof. S. Mohanthy** for providing a solid background for my studies. They have been great sources of inspiration to me and I thank them from the bottom of my heart.

I would like to thank all my friends and especially my classmates for all the thoughtful and mind stimulating discussions we had, which prompted us to think beyond the obvious. I’ve enjoyed their companionship so much during my stay at NIT, Rourkela.

I would like to thank all those who made my stay in Rourkela an unforgettable and rewarding experience.

Last but not least I would like to thank my parents, who taught me the value of hard work by their own example. They rendered me enormous support being apart during the whole tenure of my stay in NIT Rourkela.

Vedavrath Lakide

CONTENTS

ABSTRACT

The prime objective of this thesis work is to devise novel methodologies for classification of Synthetic Aperture Radar (SAR) images. Classification of SAR images has extensive applications in national economy and military field. An analyst attempts to classify features in an SAR image by using the elements of visual interpretation to identify homogeneous groups of pixels that represents various features or land cover classes of interest. The SAR images, totally different from optical images, i.e. photographs, and their visual interpretation is not straightforward. Therefore, there is need to devise novel strategies for classification of SAR images.

Common classification procedures can be broken down into two broad subdivisions based on the method used such as supervised classification and unsupervised classification. SAR image classification based on unsupervised learning usually requires optimization of some metrics. Local optimization techniques frequently fail because functions of these metrics with respect to transformation parameters are generally nonconvex and irregular and, therefore, global methods are often required.

In this thesis, SAR image classification problem is considered as an optimization problem various clustering techniques are addressed in literature for SAR image classification. This thesis focuses on an evolutionary based stochastic optimization technique that is Particle Swarm Optimization (PSO) technique for classification of SAR images. This technique composes of three main processes: firstly, selecting training samples for every region in the SAR image. Secondly, training these samples using PSO, and obtain cluster center of every region. Finally, the classification of SAR image with respect to cluster center is obtained. To show the effectiveness of this approach, classified SAR images are obtained and compared with other clustering techniques such as K-means algorithm and Fuzzy C-means algorithm (FCM). The performance of PSO is found to be superior than other techniques in terms of classification accuracy and computational complexity. The result is validated with various SAR images.

LIST OF FIGURES

LIST OF TABLES

ABBREVIATIONS USED

SAR	Synthetic Aperture Radar
FCM	Fuzzy c-means algorithm
ML	Maximum Likelihood
NN	Neural Networks
RAR	Real Aperture Radar
PSO	Particle Swarm Optimization

CHAPTER 1

INTRODUCTION

1.1 INTRODUCTION

Environmental monitoring, earth-resource mapping, and military systems require broad-area imaging at high resolutions. Many times the imagery must be acquired in inclement weather or during night as well as day. Synthetic Aperture Radar (SAR) provides such a capability. SAR systems take advantage of the long-range propagation characteristics of radar signals and the complex information processing capability of modern digital electronics to provide high resolution imagery. Synthetic aperture radar complements photographic and other optical imaging capabilities because of the minimum constraints on time-of-day and atmospheric conditions and because of the unique responses of terrain and targets to radar frequencies.

Synthetic Aperture Radar is a radar technology that is used from satellite or airplane. It produces high resolution images of earth's surface by using special signal processing techniques. Synthetic aperture radar has important role in gathering information about earth's surface because it can operate under all kinds of weather condition (whether it is cloudy, hazy or dark).However acquisition of SAR images face certain problems**.**

1.1.1 SYNTHETIC APERTURE RADAR (SAR)

SAR began with an observation by Carl Wiley in 1951 that a radar beam oriented obliquely to the radar platform velocity vector will receive signals having frequencies offset from the radar carrier frequency due to the Doppler Effect [1]. Synthetic-aperture radar (SAR) is a type of radar it is shown in Fig 1.1(a) and Fig1.1 (b) in which a large, highly-directional rotating antenna used by conventional radar is replaced with many low-directivity small stationary antennas scattered over some area near or around the target area. The many echo waveforms received at the different antenna positions are post-processed to resolve the target. Synthetic-aperture radar (SAR) can only be implemented by moving one or more antennas over relatively immobile targets, by placing multiple stationary antennas over a relatively large area, or combinations thereof.

In a typical SAR application, a single radar antenna is attached to the side of an aircraft. A single pulse from the antenna will be rather broad because diffraction requires a large antenna to produce a narrow beam. The pulse will also be broad in the vertical direction; often it will illuminate the terrain from directly beneath the aircraft out to the horizon. If the terrain is approximately flat, the time at which echoes return allows points at different distance to be distinguished. Distinguishing points along the track of the aircraft is difficult with a small antenna. However, if the amplitude and phase of the signal returning from a given piece of ground are recorded, and if the aircraft emits a series of pulses as it travels, then the results from these pulses can be combined. An appropriate coherent combination of several pulses leads to the formation of a synthetically enlarged antenna - the so-called **` Synthetic Aperture'.** Maximum synthetic aperture size is the maximum distance traveled while target is illuminated.

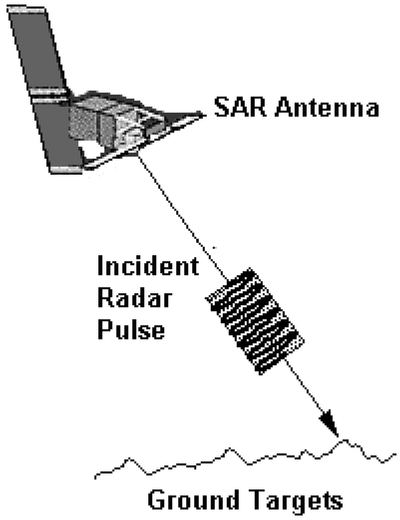


Fig 1.1(a) A radar pulse is transmitted From the Antenna to the ground.

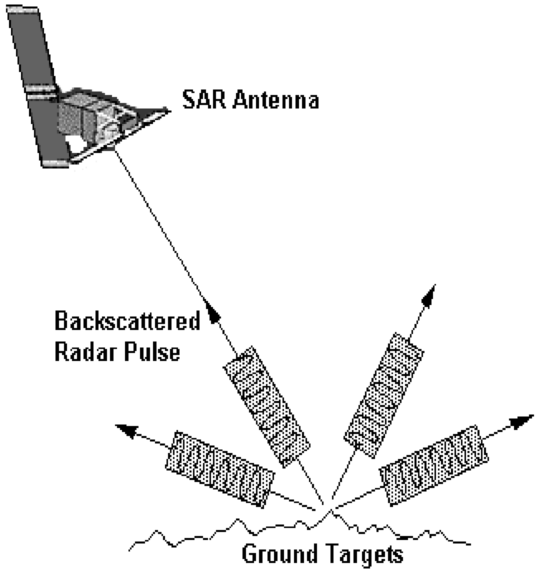


Fig 1.1(b) The radar pulse is scattered by the Ground targets back to the antenna.

In practice, **SAR** image is formed [2] using correlative radar waves to irradiate surface of ground and gathering backwards radioactive waves, highly distinguishing-rate SAR image can be obtained. All signals reflected from a ground unit disturb each other, so there exit a great deal of stain noise. SAR images contain speckle noise which is based on multiplicative noise. Speckle noise is the result of two phenomenon, first phenomenon is the coherent summation of the backscattered signals and other is the random interference of electromagnetic signals [3].Speckle noise degrades the appearance and quality of SAR images.

1.1.2 Basic principles of SAR

The principle of aperture synthesis [4] is storing successive echoes obtained from radar carried by a moving platform, and processing them to synthesize a long aperture, thereby achieving high-resolution images. SARs and other conventional RARs achieve range resolution in the same way by using the pulse ranging technique. However, SARs can improve along-track resolution by using aperture synthesis it is shown in Fig1.2. The real aperture azimuthal resolution is a function of the radar wavelength, target range, and antenna dimension as shown by the equation (1.1).

$$\delta_{AT} = \frac{\lambda}{D_{AT}} R \text{......... } 1.1$$

Where λ is the wavelength, D_{AT} is the antenna length in the along-track direction and R is the range from the radar to the target.

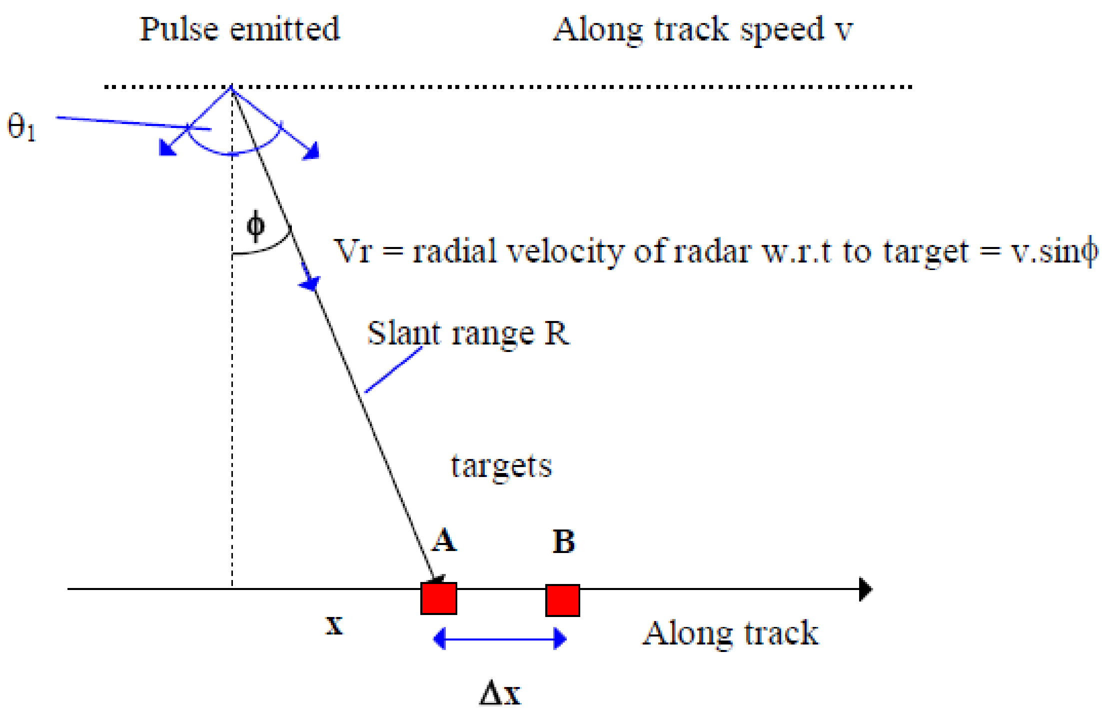


Figure 1.2 Resolution Improvement along Track

1.1.3 Image Processing and Analysis

Digital Image Processing is a collection of techniques for the manipulation of digital images by computers. The raw data received from the imaging sensors on the satellite platforms or aircrafts contains flaws and deficiencies. To overcome these flaws and deficiencies in order to get the originality of the data, it needs to undergo several steps of processing. This will vary from image to image depending on the type of image format, initial condition of the image and the information of interest and the composition of the image scene. Digital Image Processing undergoes three general steps:

i. Pre-processing
ii. Display and enhancement
iii. Information extraction

Pre-processing consists of those operations that prepare data for subsequent analysis that attempts to correct or compensate for systematic errors. The digital imageries are subjected to several corrections such as geometric, radiometric and atmospheric, though all these corrections might not be necessarily be applied in all cases. These errors are systematic and can be removed before they reach the user. The investigator should decide which pre-processing techniques are relevant on the basis of the nature of the information to be extracted from remotely sensed data. After pre-processing is complete, the analyst may use feature extraction to reduce the dimensionality of the data. Thus feature extraction is the process of isolating the most useful components of the data for further study while discarding the less useful aspects (errors, noise etc).

Image Enhancement operations are carried out to improve the interpretability of the image by increasing apparent contrast among various features in the scene.

As an image enhancement technique often drastically alters the original numeric data, it is normally used only for visual (manual) interpretation and not for further numeric analysis. Common enhancements includes transect extraction, contrast adjustments, spatial filtering, Fourier transformations, etc.

Information Extraction is the last step toward the final output of the image analysis. After pre-processing and image enhancement the remotely sensed data is subjected to quantitative analysis to assign individual pixels to specific classes. Classification of the image is based on the known and unknown identity to classify the remainder of the image consisting of those pixels of unknown identity. After classification is complete, it is necessary to evaluate its accuracy by comparing the categories on the classified images with the areas of known identity on the ground. The final result of the analysis consists of maps (or images), data and a report. These three components of the result provide the user with full information concerning the source data, the method of analysis and the outcome and its reliability.

1.1.4 Features of SAR

1. A large effective antenna aperture is obtained by mounting the antenna on a moving platform-an aircraft or a satellite.
2. Resolutions of down to 10m can be obtained, so that images of the earth's surface can be generated.
3. Complex signal processing is required to extract images, so that real-time operation makes heavy demands on computer processing power.
4. Very large amounts of data are generated - as can be seen if say 10 items of information are generated for each $10m^2$ of the earth's surface.

1.1.5 Applications

Synthetic-aperture radar (SAR) has seen wide applications in remote sensing and mapping. Synthetic aperture radar technology has provided terrain structural information to geologists for mineral exploration, oil spill boundaries on water to environmentalists, sea state and ice hazard maps to navigators, and reconnaissance and targeting information to military operations. There are many other applications or potential applications. Some of these, particularly civilian, have not yet been adequately explored because lower cost electronics are just beginning to make SAR technology economical for smaller scale uses. Imaging techniques now form an important part of radar use, and high resolution images from aircraft and satellites are used for remote sensing and environmental monitoring, as well as for military surveillance.

1.2 MOTIVATION

Synthetic Aperture Radar (SAR) image classification is becoming increasingly important in military or scientific research. SAR image processing is commonly recognized as a hard task because of high dynamics and multiplicative noise takes place, which prevent the use of classical image processing tools. Classification methods based on thresholding of gray levels are generally inefficient when applied to speckled images, due to the high degree of overlap between the distributions of the different classes. Speckle is caused by the constructive and destructive interference between waves returned from elementary scatterers within each resolution cell. It is generally modeled as a multiplicative random noise [4], [3].

The model based approaches are used to classify the SAR images are 1.*supervised approach*, 2.*unsupervised approach*. In *supervised frame* work, the associated model parameters are assumed to be known apriori. In unsupervised frame work the parameters assumed to be unknown. The motivation of this dissertation is to develop a classification algorithm for clustering which can be used to classify the SAR images and improving overall accuracy. To show the improvement of classification accuracy the PSO classified results are compared with standard K-means algorithm and FCM algorithm. The advantage of PSO algorithm is initial conditions are not required and it performs a globalized searching for solutions whereas most other partitional clustering procedures perform a localized searching.

1.3 LITERATURE REVIEW

Both visual interpretation and automatic analysis of data from imaging radars are complicated by a fading effect called speckle, which manifests itself as a strong granularity in detected images (amplitude or intensity). For example, simple classification methods based on thresholding of gray levels are generally inefficient when applied to speckled images, due to the high degree of overlap between the distributions of the different classes. Speckle is caused by the constructive and destructive interference between waves returned from elementary scatterers within each resolution cell. It is generally modeled as a multiplicative random noise [4], [3]. Compared with optical image, **SAR** image has more legible outline, better contrast and more plentiful texture information [2]. The objects of different shape and physical feature take on different texture character, which is a critical technique of identifying objects by radar. At present, there are many approaches to image classification, but there is not an approach to suit all kinds of images. During the past years, different methods were employed for classification of synthetic aperture radar (SAR) data [5-6], based on the

Maximum Likelihood (ML) [5], artificial Neural Networks (NN) [7], fuzzy methods [8, 9] or other approaches [6-9]. The NN classifier depends only on the training data and the discrimination power of the features. Fukuda and Hirosawa [10] applied wavelet-based texture feature sets for classification of multi frequency polarimetric SAR images. The Classification accuracy depends on quality of features and the employed classification algorithm.

For a high resolution SAR image classification, there is a strong need for statistical models of scattering to take into account multiplicative noise and high dynamics. For instance, the classification process needs to be based on the use of statistics. Clutter in SAR images becomes non-Gaussian when the resolution is high or when the area is man-made. Many models have been proposed to fit with non-Gaussian scattering statistics (Weibull, Log normal, Nakagami Rice, etc.), but none of them is flexible enough to model all kinds of surfaces in our context [11].

For SAR image classification problem many fuzzy models have been proposed, Fuzzy c-means clustering (FCM) algorithm [12] is widely applied in various areas such as image processing and pattern recognition. Co-occurrence matrix and entropy calculations are used to extract transition region for an image. This transition region approach [12] is used to classify the SAR images.

1.4 CONTRIBUTION OF THESIS WORK

The contribution of this thesis can be summarized as follows. The thesis presents a different approach, to solve the classification problem of SAR images. SAR image classification based on unsupervised learning usually requires optimization of some metrics. Local optimization techniques frequently fail because functions of these metrics with respect to transformation parameters are generally nonconvex and irregular and, therefore, global methods are often required. The traditional clustering methods are very sensitive to the initial value and the number of clusters. The accurate initial value and number of clusters are important parameters to get the accurate result. The traditional algorithm of FCM applies directly SAR image to get the ideal result difficultly. So a novel algorithm, particle swarm optimization is used for SAR image classification. To show the effectiveness of this approach, simulation results of classified SAR images are considered and compared with K means algorithm According to the overall accuracy, PSO has high classification precision and can be used in SAR images classification efficiently.

1.5 ORGANIZATION OF THESIS

The thesis is organized into the following chapters

Chapter 1 (Introduction): deals with the formal description of the SAR image formation, basics of SAR image processing and analysis and problem of SAR image classification and the related research work already carried out in this direction. The addressed problem is also included here.

Chapter 2 (Background of K-means and Fuzzy C-Means Algorithm): introduces the basic definitions and concepts of fuzzy data sets and Fuzzy c-means clustering technique that will be needed in the further chapters. It also includes the fuzzy c-means algorithm with its examples, strengths and weakness.

Chapter 3 (Synthetic aperture radar Image classification using particle swarm optimization technique): This chapter mainly focuses on the Particle Swarm Optimization Technique, classification of Synthetic Aperture Radar images using Particle Swarm Optimization and PSO algorithm steps for image classification.

Chapter 4 (Classification accuracy assessment): In this chapter accuracy assessment procedure is described.

Chapter 5 (Simulations and Results): covers discussions on the simulation results of SAR images.

Chapter 6 (Conclusion): includes the conclusion and the discussion for future research.

CHAPTER2

BACKGROUND OF K-MEANS AND FUZZY C-MEANS ALGORITHM

2.1 INTRODUCTION

In this Chapter, the basic K-means algorithm and Fuzzy C-means (FCM) algorithms are described. Both K-means and Fuzzy c-means algorithms are *clustering* algorithms. Clustering can be considered as the most important unsupervised learning problem. So, as every other problem of this kind, it deals with finding a structure in a collection of unlabeled data.

A classical set is a set that has a crisp boundary. For example, a classical set X of real numbers greater than 6 is expressed as

$$A = \{x \mid x > 6\}$$

In this set of real numbers there is a clear unambiguous boundary 6 such that if x is greater than this number. In this case x either belongs to this set *'A'* or it does not belong to this set. These types of sets are called Classical Sets and the elements in this set are a part of the set or they are not a part of the set. Classical sets are an important tool in mathematics and computer science but they do not reflect the nature of human concepts and thought.

In contrast to a classical set, a fuzzy set is a set without crisp boundaries. That is, the process of an element "belongs to a set" to "does not belong to a set" is gradual. This transition is decided by the membership function of a fuzzy dataset. Real life problems have data which most of the time has a degree of "trueness" or "falseness" that is the data cannot be expressed in terms of classical set. A good example of this is; the same set A is a set of tall basketball players. According to the classical set logic a player 6.01 ft tall is considered to be tall whereas a player 5.99 ft tall is considered to be short.

2.1.1. Fuzzy Sets and Membership Function

Membership functions give fuzzy sets the flexibility in modeling commonly used linguistic terms such as "the water is hot" or "the temperature is high." Zadeh (1965) points out that, this imprecise data set information plays an important role in human approach to problem solving. It is important to note that fuzziness in a dataset comes does not come from the randomness of the elements of the set, but from the uncertain and imprecise nature of the abstract thoughts and concepts.

If X is a collection of objects denoted by x, then a fuzzy set *'A'* in *'X'* is defined as a set of ordered pairs

$$A = \{(x, \mu A\,(x)) \mid x \in X\},$$

Where $\mu A(x)$ is called the membership function (MF) for the fuzzy set A. The membership function maps each element of X to a membership grade between 0 and 1. If the value of the membership function is restricted to either 0 or 1, then A is reduced to a classical set and $\mu A(x)$ is the characteristic function of A. Usually X is referred to as the universe of discourse and may consist of discrete objects or continuous space.

2.2 DATA CLUSTERING ALGORITHMS

A loose definition of clustering could be "the process of organizing objects into groups whose members are similar in some way". A *cluster* is therefore a collection of objects which are "similar" between them and are "dissimilar" to the objects belonging to other clusters. Clustering of numerical data forms the basis of various classification and system modeling algorithms. The purpose of clustering is to identify natural groupings of data from a large data set to produce a concise representation of a system's behavior. Clustering algorithms are not only used to organize and categorize data, but are helpful in data compression and model construction.

The clustering algorithms can be categorized into two groups: hierarchical and Partitional [13], [14]. In hierarchical clustering, the output is "a tree showing a sequence of clustering with each clustering being a partition of the data set". The partitional clustering algorithms partition the data set into a specified number of clusters. These algorithms try to minimize certain criteria (e.g. a square error function); therefore, they can be treated as an optimization problem.

2.3. K MEANS CLUSTERING ALGORITHM

The K-means clustering, also known as C-means clustering, has been applied to variety of areas, including image and speech data compression. The *k*-means clustering was invented in 1956. This technique is based on randomly choosing *k* initial cluster centers, or means. These initial cluster centers are updated in such a way that after a number of cycles they represent the clusters in the data as much as possible. The K-means algorithm starts with K- cluster centers or centriodes. Cluster centriodes can be initialized to random values or can be derived from a priori information. Each data point then assigned to the closest cluster (i.e. closest centroide). Finally, the centriodes are recalculated according to the associated data. This process is repeated until convergence.

K-means clustering groups' data vectors into a predefined number of clusters, based on Euclidean distance as similarity measure. Data vectors within a cluster have small Euclidean distances from one another, and are associated with one centroide vector, which represents the "midpoint" of that cluster. The centroide vector is the mean of the data vectors that belong to the corresponding cluster.

1. The algorithm starts out with initializing *Ci* this is achieved by randomly Selecting *C* points from among all the data points.
2. The algorithm starts out with initializing *Ci* this is achieved by randomly Selecting *C* points from among all the data points.
3. Determine the membership matrix U, where the element *uij* is 1 if the *j*th data point x*j* belongs to the group 1 and 0 otherwise.
4. Compute the cost function by the equation given below. Stop if the value of cost function is below a certain threshold value.

$$J = \sum_{i=1}^{c} J_i = \sum_{i=1}^{c} \left(\sum_{k, X_k \in c_i} ||X_k - C_i||^2 \right)$$

5. Assign each data point to the cluster closest centroide.
6. Update the clusters center centers *Ci* by re calculating the clusters centriodes as mean of all data points within the each cluster *and* determine the new *U* matrix.

Parameters and options for the k-means algorithm: Number of classes, Initialization, Distance measure, Termination.

Drawbacks of the *k*-means algorithm are that the number of clusters is fixed; once *k* is chosen it always remains *k* cluster centers. The K-means algorithm circumvents the problem by removing the redundant clusters. Whenever a cluster centre is not assigned enough samples, it may be removed. In this way one is left with a more or less optimal number of clusters. The problem of choosing the initial number of clusters still remains unsolved, but by taking *k* large enough this will usually not be a problem. For the analysis of large datasets—the method is computationally inefficient. Each step of the procedure requires calculation of the distance between every possible pair of data points and comparison of all the distances. It is a greedy algorithm that depends on the initial conditions, which may cause the algorithm to converge to suboptimal solutions.

2.4. HIERARCHICAL CLUSTERING ALGORITHM

In hierarchical clustering the data is not partitioned into a particular cluster in a single step. Instead, a series of partitions takes place that run from a single cluster containing all objects to *N* clusters each containing a single object. Hierarchical clustering is further classified as agglomerative method, which proceed by series of fusions of the *N* objects into groups, and divisive method, which separate *N* objects successively into finer groupings. Hierarchical clustering may be represented by a two-dimensional diagram known as dendrogram, which illustrates the fusion or divisions made at each successive stage of analysis. Given a set of *N* items to be clustered, and an NxN distance matrix, the basic process of Johnson's (1967) hierarchical clustering is briefly explained below.

1. The algorithm starts by assigning each item to its own cluster, such that for *N* items, we have N clusters, each containing just one item. Let the distances between the clusters equal the distances between the items they contain.
2. Find the closest (most similar) pair of clusters and merge them into a single cluster, so that we have one less cluster.
3. Compute distances between the new cluster and each of the old clusters.
4. Repeat steps 2 and 3 until all items are clustered into a single cluster of size N.

Step 3 can be done in different ways, which is what distinguishes single-link from complete-link and average-link clustering. In single-link, clustering (also called the connectedness or minimum method); we consider the distance between one cluster and another cluster to be equal to the shortest distance from any member of one cluster to any member of the other cluster. If the data consist of similarities, we consider the similarity between one cluster and another cluster to be equal to the largest similarity from any member of one cluster to any member of the other cluster. In complete-link, clustering (also called the diameter or maximum method); we consider the distance between one cluster and another cluster to be equal to the longest distance from any member of one cluster to any member of the other cluster. In average-link clustering, we consider the distance between one cluster and another cluster to be equal to the average distance from any member of one cluster to any member of the other cluster.

Today, Synthetic Aperture Radar (SAR) image classification is becoming increasingly important in military or scientific research. The large amount of data involved necessitates the identification or *segmentation* of the objects of interest before further analysis can be made. The result of this segmentation or classification process is the labeling or grouping of pixels into meaningful regions or classes. There is a very strong intuitive similarity between clustering and segmentation; both processes share the goal of finding accurate classification of their input. Fuzzy clustering, therefore, has been used for image segmentation for the past twenty years. FCM's objective function has been generalized and extended as well as changed in several ways. For this reason, FCM is sometimes described as a model for fuzzy clustering. Our aim in this Chapter will be to define and describe the FCM model. We also highlight the strengths and shortcomings that this algorithm. In the next Chapter, we propose our particle swarm optimization technique for SAR image classification.

2.5. THE FUZZY C-MEANS ALGORITHM

Fuzzy C-means clustering (FCM) algorithm, also known as fuzzy Isodata, is a data clustering algorithm in which each data point belongs to a cluster to a degree specified by a membership grade. Bezdek proposed this algorithm in 1973 as an improvement to K means algorithm also known as the hard C-means algorithm. Hard k-means algorithm executes a sharp classification, in which each object is either assigned to a class or not. The application of fuzzy clustering to the dataset function allows the class membership to have several classes at the same time but with different degrees of membership function ranging from 0 to 1. Fuzzy c-means (FCM) is a method of clustering which allows one piece of data to belong to two or more clusters. It is based on minimization of the objective function

2.5.1. FCM Optimization Model

The formulation of the FCM optimization model is:-

Minimize $J_{fcm}(U,V;X,c,m) = \sum_{i=1}^{c}\sum_{k=1}^{N}(u_{ik}^{m})d_{ik}^{2}(X_k,V_i)$ (2.1)

Subject to the constraint $\sum_{i=1}^{c} u_{ik} = 1 \quad \forall\, k \in \{1,2,\dots,N\}$ (2.2)

Where U and V are the variables whose optimal values are being sought. X, c and m are input parameters of J_{fcm} where:-

- c is the number of clusters assumed to exist in X.
- $m \geq 1$ is a fuzzification exponent that controls how fuzzy the result will be. The larger the value of m the fuzzier the solution. At m=1 1FCM collapses to HCM, giving crisp results. At very large values of m, all the points will have equal memberships with all the clusters.

- u_{ik} describes the degree of membership of feature vector X_k with the cluster represented by V_i. $U = [u_{ik}]$ is the $c \; x \; N$ Fuzzy partition matrix satisfying the constraint stated in (2.2).
- N is the total number of feature vectors.
- d_{ik}^2 is the distance between feature vector X_k and prototype V_i. The original formulation of FCM uses point prototypes and an inner-product induced-norm metric for d_{ik}^2 given by

$$d_{ik}^2(X_k, V_i) = \|X_k - V_i\|_A^2 = (X_k - V_i)^T A (X_k - V_i) \qquad (2.3)$$

A is any positive definite matrix which in the case of Euclidean distance is the identity matrix.

2.5.2. Conditions for Optimality

Let the minimisers of $J_{fcm}(U, V)$ called (U^*, V^*) . The necessary conditions for (U^*, V^*) are defined and derived below.

Membership evaluation:

We compute this using Lagrange multiplier as shown below

$$F_m = \sum_{i=1}^{c} \sum_{k=1}^{N} u_{ik}^m d_{ik}^2 + \lambda\left(1 - \sum_{j=1}^{c} u_{jk}\right) \qquad (2.4)$$

Taking the derivative of F_m with respect to u_{ik} and setting the result to zero, we have:

$$\left[\frac{\partial F_m}{\partial u_{ik}} = m u_{ik}^{m-1}(d_{ik}^2) - \lambda\right]_{u_{ik}=u_{ik}^*} = 0 \qquad (2.5)$$

Solving for u_{ik}^* we have:

$$u_{ik}^* = \left(\frac{\lambda}{m d_{ik}^2}\right)^{1/m-1} \qquad (2.6)$$

Since $\sum_{j=1}^{c} u_{jk} = 1$ for $\forall$ k we have:

$$\sum_{j=1}^{c} \left(\frac{\lambda}{m d_{ik}^2}\right)^{1/m-1} = 1 \qquad (2.7)$$

or

$$\lambda = \frac{m}{\left(\sum_{j=1}^{c}\left(\frac{1}{d_{jk}^2}\right)^{1/m-1}\right)^{m-1}} \qquad (2.8)$$

Substituting the above equation into (2.6), the zero-gradient condition for the membership estimator can be rewritten as:

$$u_{ik}^{*} = \frac{1}{\sum_{j=1}^{c}\left(\frac{d_{ik}^{2}}{d_{jk}^{2}}\right)^{1/m-1}} \qquad (2.9)$$

Cluster prototype updating:

Taking the derivative of J_{fcm} with respect to v_i and setting the result to zero, we have:

$$\left[\sum_{k=1}^{N} \frac{\partial}{\partial V_i} u_{ik}^{m}(x_k - v_i)^2\right]_{V_{i=V_i^*}} = 0 \qquad (2.10)$$

$$[\sum_{k=1}^{N} 2\ u_{ik}^{m}\,(x_k - v_i)]_{v_{i=v_i^*}} = 0 \qquad (2.11)$$

$$[\sum_{k=1}^{N} u_{ik}^{m}\,x_k - \sum_{k=1}^{N} u_{ik}^{m}\,v_i]_{v_{i=v_i^*}} = 0 \qquad (2.12)$$

Solving for v_i, we have:

$$v_i^{*} = \frac{\sum_{k=1}^{N} u_{ik}^{m}\ x_k}{\sum_{k=1}^{N} u_{ik}^{m}} \qquad (2.13)$$

The FCM algorithm is a sequence of iterations through the equations (2.9), (2.13), which are referred to as the update equations. When the iteration converges, a fuzzy c-partition matrix and the pattern prototypes are obtained.

2.5.3 Fuzzy C-Means Algorithm

1.fix c, 2≤c≤N,m,1≤m≤∞ initialize The class prototypes V

2. Compute the partition matrix using (2.9).

3. Update fuzzy cluster centers V using (2.13).

4. Compare the change in the cluster centers values using a appropriate norm; if the change is Small, stop. Else return to 2.

2.5.4. Fuzzy Factor

The fuzzy factor ‘m’ was introduced by Bezdek and is also known as ‘fuzzifier’ As the value of m approaches 1 the clusters formed tend to be hard and as the value of m tends to infinity the obtained clusters tend to go in a the fuzziest state. There is no theoretical justification on the value of ‘m’ but is usually set to 2 and in a more generalized form tends to be between 1.5 and 3 (Zimmermann, 1990).

2.5.5. Ideal Number of Clusters ‘c’

From the research on decision of ideal number of clusters for the FCM algorithm, they find out that there is nothing called as an ideal number of clusters (Zimmermann, 1990). The number of clusters for a certain type of data will vary based on the data partition desired. The number of clusters can vary between 2 to infinity.

2.5.6. Significance of Membership Function in Cluster Analysis

As discussed in the earlier section, data are bound to each cluster by means of a membership function, which represents the fuzzy behavior of this algorithm. To do that, we build an appropriate matrix named U whose factors are numbers between 0 and 1, and represent the degree of membership between data and centers of clusters. In the FCM approach, instead, the same given datum does not belong exclusively to a well-defined cluster, but it can be placed in a middle way. In the case of FCM, the membership function follows a smoother line to indicate that every datum may belong to several clusters with different values of the membership coefficient.

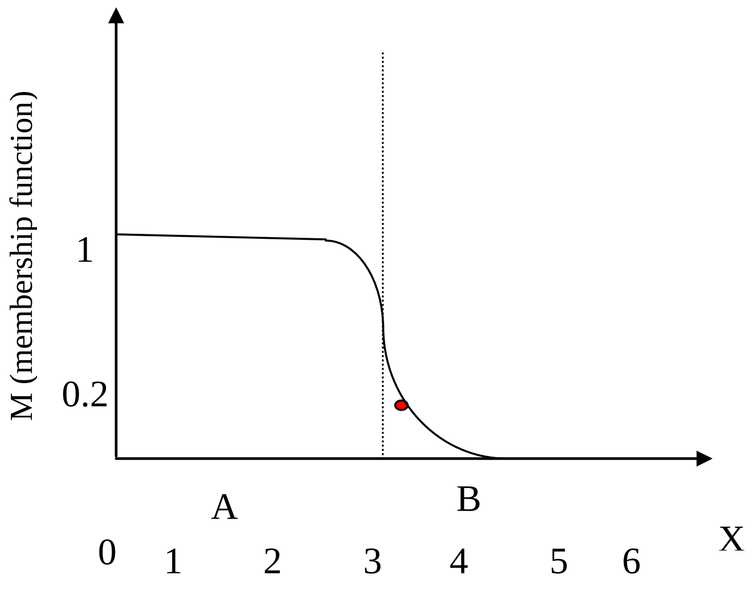


Fig 2.1 Membership Function for FCM Algorithm

In Fig 2.1 (George and Yuan, 1995), the datum shown as a red marked spot belongs more to the cluster B rather than the cluster A. The value 0.2 of membership function indicates the degree of membership to A for such datum. Now, instead of using a graphical representation, we introduce a matrix U_{NxC} whose factors are the ones taken from the membership functions. The number of rows and columns depends on how many data and clusters we are considering. Here C (columns) is the total number of clusters and N (rows) is the total data points.

$$U_{NxC} = \begin{pmatrix} 0.8 & 0.2 \\ 0.3 & 0.7 \\ 0.6 & 0.4 \\ . & . \\ . & . \\ 0.9 & 0.1 \end{pmatrix}$$

2.6. STUDY OF FUZZY C-MEANS ALGORITHM

Let us give an example of FCM in action. Figure 2.2shows the data set that we used as input to FCM (c=2). The table.1 tabulates the found partition matrix. Whereas the solution is an approximately correct one, the locations of the found prototypes are not satisfactory since they should be at the centres of the diamond like patterns. It is clear that the points located away from the diamond patterns have influenced FCM's solution in that they have "pulled" the prototypes away from the ideal locations. We note that, as expected, the membership values per each point add up to one.

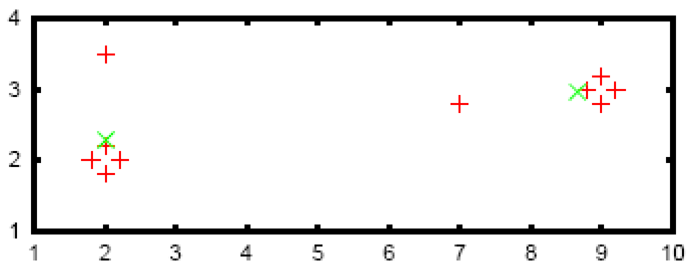


Fig 2.2 A 10-point data set with two clusters and two outlying points.

Input data points are marked with a '+' and the prototypes found by FCM are marked with 'x'. Membership values provided by FCM are tabulated in the given below (Table 2.1). The found prototypes are at (2.0; 2.2) and (8.7; 3.0) instead of ideal placement at (2.0; 2.0) and (9.0; 3.0).

Table 2.1 Membership values of the data

Data		Memberships	
x	y	Cluster1	Cluster2
1.8	2	0.997	0.003
2.0	2.2	1.000	0.000
2.0	1.8	0.995	0.005
2.2	2	0.997	0.003
2.0	3.5	0.968	0.032
8.8	3	0.000	1.000
9.0	3.2	0.003	0.997
9.0	2.8	0.003	0.997
9.2	3	0.006	0.994
7	2.8	0.100	0.900

2.6.1. Analysis of FCM Model

FCM generalized the notion of membership to emulate the fuzzy clustering structures found in the real-world. The FCM objective function weighted the distance between a given data point and a given prototype by the corresponding degree of membership between the two (the respective entry in the fuzzy partition matrix). Thus, partitions that minimize this function are those that weight small distances by high membership values and large distances by low membership values. This was formulated as per (2.1). To visualize this, consider Fig 2.3. If point 6 is given a high membership value with prototype B as compared to points 2 and 3, the overall objective function score will be minimal compared to any other membership scheme involving those three points and that prototype.

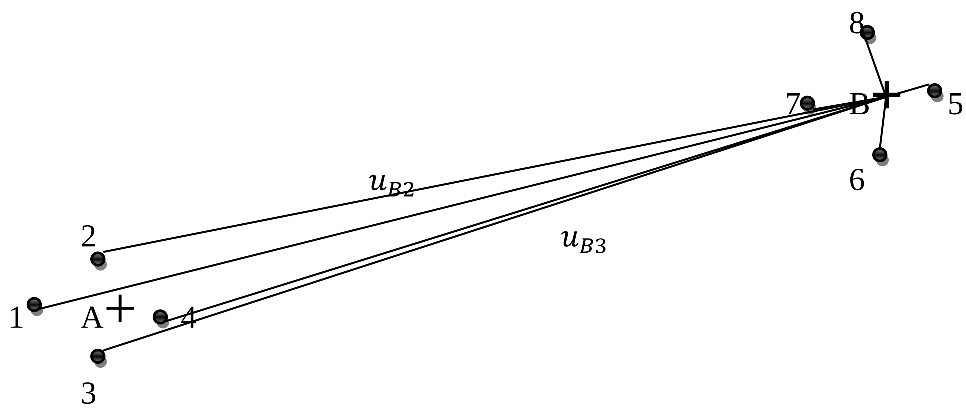


Fig 2.3 Distance of the Points from centriodes

The distances between points 1……8 and prototypes A and B are weighted by the degrees of memberships. Here, the distances and memberships concerning only prototype B are shown. However, if things were left at the objective function formulation, without the constraint of (2.2), all the u_{ik}'s would take the value of zero as this would set J_{fcm} to the absolute minimal value of zero, which is a trivial solution. In order to force the u_{ik}'s to take values greater than zero, the constraint was imposed. This way, degrees of membership must take non-trivial values. Looking now at the minimisers of the objective function, (2.9) and (2.13), we see that the prototypes are the fuzzy centroids, or means, of their respective membership function. This is an intuitively-pleasing result. Further, we see that a point's membership with a given prototype is affected by how far that same point is to the other prototypes. This is illustrated in Fig 2.3, where

$$u_{ax} = \frac{1}{1+\left(\frac{d_{ax}^2}{d_{bx}^2}\right)^{\left(1/_{m-1}\right)}} \tag{2.14}$$

This may cause counter-intuitive behavior in real-world data. If we observe Figure 2.3, we notice that a point's membership degree is not a function of anything but its relative distances to each prototype.

2.6.2. Strengths

The FCM algorithm has proven a very popular method of clustering for many reasons. In terms of programming implementation, it is relatively straightforward. It employs an objective function that is intuitive and easy-to-grasp. For data sets composed of hyper spherically-shaped well-separated clusters, FCM discovers these clusters accurately. Furthermore, because of its fuzzy basis, it performs robustly: it always converges to a solution, and it provides consistent membership values.

2.6.3. Weaknesses

FCM technique has been used for classification of SAR images. But this method introduced some errors in the classification results and was found to be very sensitive to initial cluster centers.

CHAPTER3

SYNTHETIC APERTURE RADAR IMAGE CLASSIFICATION USING PARTICLE SWARM OPTIMIZATION TECHNIQUE

3.1. INTRODUCTION

This chapter mainly focuses on the Particle Swarm Optimization Technique, classification of Synthetic Aperture Radar images using Particle Swarm Optimization and PSO algorithm steps for image classification.

3.1.1. Particle Swarm Optimization Technique

Particle Swarm Optimization is a population based stochastic optimization technique inspired by the social behavior of bird flock (and fish school etc.), as developed by Kennedy and Eberhart in 1995 [15]. Some of the attractive features of the PSO include the ease of implementation and the fact that no gradient information required. It can be used to solve a wide array of different optimization problems. Many optimization algorithms are deterministic like gradient-based algorithms. The PSO belongs to evolutionary algorithm family it does not need gradient information derived from the error function. This allows the PSO to be used on functions where the gradient is either unavailable or computationally expensive to obtain.

Particle Swarm Optimization (PSO) is a relatively new population-based evolutionary computation technique [16] [22]. PSO [17] is initialized with a group of random particles (solutions) and then searches for optima by updating generations. In every iteration, each particle is updated by following two "best" values. The first one is the best solution (fitness) it has achieved so far. (The fitness value is also stored.) This value is called P_{best}. Another "best" value that is tracked by the particle swarm optimizer is the best value, obtained so far by any particle in the population. This best value is a global best and called g_{best}. When a particle takes part of the population as its topological neighbors, the best value is a local best and is called l_{best}. At each iteration, the i-th particle i = 1,2,**.....**N, (N is the number of particles) moves by addition of a velocity vector v_i, which is a function of the best position p_i found by that particle, and of the best position 'g' found so far among all particles. x_i, v_i, p_i and 'g' are D-dimensional vectors. At iteration t, the position of the i-th particle is given as

$$v_i(t) = w(t)v_i(t-1) + c_1 \times r_1 \times (p_i - x_i(t-1)) + c_2 \times r_2 \times (g - x_i(t-1)) \quad \text{..........3.1}$$

$$x_i(t+1) = x_i(t) + v_i(t) \quad \text{..................................3.2}$$

Where $w(t)$ is the inertial weight, the c_1 and c_2 are acceleration constants, and the r $\in$ (0, 1) are uniformly distributed random numbers. To keep the x_i within reasonable bounds, velocities are often clamped to a maximum velocity v_{max}: $v_i \in [-v_{max}\ v_{max}]$. The algorithm makes use of two independent random sequences, $r_1, r_2 \in (0,1)$ these sequences used to affect the stochastic nature of the algorithm.

$$v_i(t) = w(t)v_i(t-1) + c_1 \times r_1 \times (p_i - x_i(t-1)) + c_2 \times r_2 \times (g - x_i(t-1)) \quad \ldots\ldots\ldots 3.3$$

The values of are scaled by constants $0 \le C_1, C_2 \le 2$ these constants are called the acceleration coefficients, and they influence the maximum size of the step that a particle can take in a single iteration. From the definition of the velocity update equation is clear that c_2 regularates the maximum step size in the direction of the global best particle, and c_1 regularates the maximum step size in the direction of the personal best of the particle. The velocity is clamped to the range $[-v_{max}\ v_{max}]$, to reduce the likelihood that the particle might leave the search space. if the search space is defined by the bounds $[-X_{max}, X_{max}]$, then the value of the V_{max} is typically set so that V_{max}=K* X_{max} where $0.1 \le K \le 1.0$. The position of each particle is updated using the velocity vector for that particle, so that

$$x_i(t+1) = x_i(t) + v_i(t) \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots 3.4$$

It is important to realize that the velocity term models the rate of change in the position of the particle. The change induced by the velocity update equation (3.3) there represents acceleration, which explains why the constants c_1 and c_2 are called acceleration coefficients. A brief description of how the algorithm works is as follows: Initially, some particles are identified as the best particles in a neighborhood of particles, based on its fitness. All the particles accelerated in the direction of this particle, but also in the direction of their own best solutions that they have discovered previously. Occasionally the particles will overshoot their target, exploring the search space beyond the current best particle. All particles also have the opportunity to discover better particle en route, in which case the other particles change direction and head towards the new '*best'* particle. Since most functions have some continuity, chances are that a good solution will be surrounded by equally, or better, solutions. By approaching the current best solution from different solutions in search space, the chances are good that these neighboring solutions will be discovered by some of the particles.

3.2. SOCIAL BEHAVIOR

The velocity update equation is

$$v_i(t) = w(t)v_i(t-1) + c_1 \times r_1 \times (p_i - x_i(t-1)) + c_2 \times r_2 \times (g - x_i(t-1)) \quad \ldots\ldots.3.5$$

The third term in the velocity update equation, $c_2 \times r_2 \times (g - x_i(t-1))$, represents the *social* interaction between the particles. Social interaction between the particles is a form of cooperation.

3.2.1 Co-operation

Clearwater et al. define cooperation as follows: "Cooperation involves a collection of agents that interact by communicating information to each other while solving a problem." They further state that "The information exchanged between agents may be incorrect, and should sometimes alter the behavior of the agent receiving it."

3.3. RATE OF CONVERGENCE IMPROVEMENTS

Several techniques have been proposed for improving the rate of convergence of the PSO. These proposals usually involve changes to the PSO update equations, without changing the structure of the algorithm otherwise. This usually results in better local optimization performance, sometimes with a corresponding decrease in performance on functions with multiple local minima.

3.3.1. Inertia Weight

One of the most widely used improvements is the introduction of the '*inertia weight'* by Shi and Eberhart [18]. The '*inertia weight'* is a scaling factor associated with the velocity during the previous time step, resulting in a new velocity update equation, so that

$$v_i(t) = w(t)v_i(t-1) + c_1 \times r_1 \times (p_i - x_i(t-1)) + c_2 \times r_2 \times (g - x_i(t-1)) \quad \ldots.3.6$$

The original PSO velocity update equation can be obtained by setting $\boldsymbol{w}$**=1.** Shi and Eberhart investigated the effect of $\boldsymbol{w}$ values in the range [0, 1.4], as well as varying $\boldsymbol{w}$ over time [18]. Their results indicate that choosing $\boldsymbol{w}$ range [0.8 1.2] results in faster convergence, but that larger $\boldsymbol{w}$ values (>1.2) result in more failures to convergence.

The inertia weight can be likened to the temperature parameter encountered in simulated annealing algorithm. The simulated annealing algorithm has a process called the temperature schedule that is used to gradually decrease the temperature of the system. The higher the temperature, the greater the probability that the algorithm will explore a region outside of basin of attraction of the current local minima. Therefore an adaptive inertia weight can be seen as the equalent of a temperature schedule in the simulated annealing algorithm.

3.3.2 Acceleration constants

The acceleration coefficients, c_1 and c_2 control how far a particle will move in a single iteration. Typically these are both set to a value of 2.0, although it has been shown that setting $c_1 \neq c_2$ can lead to improved performance.

The performance of PSO is dependent on the parameter settings: inertial weight $w(t)$ acceleration constants c_1 and c_2 , the maximum number of iterations T, and the initialization of the population. The inertial weight is usually a monotonically decreasing function of the iteration T.

3.4. CLASSIFICATION OF SAR IMAGE USING PSO

Omran [19] proposed the first clustering algorithm based on Particle Swarm Optimization (PSO). In the PSO algorithm, the birds in a flock are symbolically represented as particles. These particles can be considered as simple agents “flying” through a problem space. A particle’s location in the multi-dimensional problem space represents one solution for the problem. When a particle moves to a new location, a different problem solution is generated. This solution is evaluated by a fitness function that provides a quantitative value of the solution’s utility.

3.4.1. PSO technique steps for image classification

The Particle Swarm Optimization technique composes of three main processes:

(1) Selecting training samples for every region in the SAR image.

(2) Training these samples using PSO, and obtain clustering center of every region.

(3) Finally, output the classification result of SAR image according to clustering center obtained.

The new method can be implemented as follows:

Step 1: Selecting training samples for every region in the image according to the number of classes.

Step 2: Generate the initial swarm, $X(0) = \{x_1(0), x_2(0) ...... x_m(0)\}$, generate the initial velocity. Set t=0, $fbest_i = p_{besti}$, $i = 1,2,\ldots.m,$ $fbest = g_{best}$.

Step 3: Calculate the fitness of all the particles in $X(t)$ as follows.

For SAR image classification problem, the clustering center $C = \{c_1, c_2, \ldots.. c_m\}$ is the mean value of all particles. The fitness of particle $x(t) = \{x_1(t), x_2(t) \ldots\ldots x_n(t)\}$, is defined as:

$$fitness(x(t)) = \sum_{i=1}^{n} |x_i(t) - c_i| \ldots\ldots\ldots\ldots\ldots\ldots\ldots..3.7$$

Step 4: Update position and velocity of all the particles as equation (3.1) and (3.2) and set $X(t+1)$ to be the resulting swarm

Step 5: For all the particles in $X(t+1)$, if $fitness(x_i(t)) < fbest_i$,then set

$fbest_i = fitness(x_i(t))$, $p_i = x_i(t+1)$;

if $fitness(x_i(t)) < fbest$ then $fbest = fitness(x_i(t))$, $g = x_i(t+1)$.

Step 6: If stop condition is satisfied, export $X(t+1)$ as the output of the algorithm, Stop.

Otherwise, t=t+1, go to Step 3. Here the stop condition is to set as the maximum number of iterations T.

Step 7: Get the optimal clustering center, which is the center of last swarm obtained.

Step 8: Repeat Step 2 to Step 7 for every class, get the optimal clustering center for every class.

Step 9: After training all the regions, calculate the distance between all pixels and Clustering centers, assign every pixel to one class with the least distance.

3.4.2. CONCLUSION

The objective of the PSO clustering algorithm is to obtain the proper centroids of clusters for minimizing the intra-cluster distance as well as maximizing the distance between clusters. The PSO algorithm performs a globalized searching for solutions whereas most other partitional clustering procedures perform a localized searching [20]. In localized searching, the solution obtained is usually located in the vicinity of the solution obtained in the previous step.

CHAPTER 4

CLASSIFICATION ACCURACY ASSESSMENT

4.1. INTRODUCTION

In this Chapter, accuracy assessment procedure is described. The accuracy of spatial data has been defined as “The closeness of results of observations, computations, or estimates to the true values or the values accepted as being true".

4.1.1 Accuracy Assessment

Accuracy assessment is an important step in the process of analyzing remote sensing data. Remote sensing products can serve as the basis for economical decisions. Potential users have to know about the reliability of the data when confronted with maps derived from remote sensing data. Accuracy defines "correctness"; it measures the agreement between a standard assumed to be correct and a classified image of unknown quality. If the image classification corresponds closely with the standard, it is said to be accurate. There are two forms of measuring accuracy; the first one is the using of reference map that is assumed to be the "correct" map and to be compared with the map to be evaluated. We have used the second form of accuracy, site-specific accuracy that is based on the detailed assessment between two maps at specific locations; it is possible to compile an error matrix that is necessary for any serious study of accuracy. The most common way to express classification accuracy is the preparation of an error matrix also known as confusion matrix or contingency matrix. Such matrices show the cross tabulation of the classified land cover and the actual land cover revealed by sample site results. Different measures and statistics can be derived from the values in an error matrix. The basic form of an error matrix and non statistical measures are described in 4.2.

4.2 CONFUSION MATRIX

A confusion matrix lists the values of known cover types of the reference data in the columns and of the classified data in the rows (Table 4.1). The main diagonal of the matrix lists the correctly classified pixels. One benefit of a confusion matrix is that it is easy to see if the system is confusing two classes (i.e. commonly mislabeling one as another). A confusion matrix contains information about actual and predicted classifications done by a classification system. Performance of such systems is commonly evaluated using the data in the matrix.

Table 4.1 Confusion matrix

Reference data

Classified data

K-means Classified	Ice	Water	Ground
Ice	75.8	3.7	3.3
Water	17.1	58.7	9.6
Ground	7.1	37.6	87.1

4.2.1 Overall Accuracy

One basic accuracy measure is the ***overall accuracy***, which is calculated by dividing the correctly classified pixels (sum of the values in the main diagonal) by the total number of pixels checked. Besides the overall accuracy, classification accuracy of individual classes can be calculated in a similar manner. Two approaches are possible:

- ***Producer's accuracy***
- ***User's accuracy***

Producer's accuracy

The ***producer's accuracy*** is derived by dividing the number of correct pixels in one class divided by the total number of pixels as derived from reference data (column total in confusion matrix Table). The producer's accuracy measures how well a certain area has been classified. It includes the error of omission which refers to the proportion of observed features on the ground that is not classified in the map. The more errors of omission exist, the lower the producer's accuracy.

Producer's accuracy (%) = 100% − error of omission (%)……… (4.1)

User's Accuracy

The ***user's accuracy*** is defined by the measure of the correct classified pixels in a class divided by the total number of pixels that were classified in that class (row total in confusion matrix Table). The user's accuracy is, therefore, a measure of the reliability of the map. It informs the user how well the map represents what is really on the ground. It includes the error of commission, which refers to the proportion of the predicted features of the classification on the map that are not observed on the ground. The more errors of commission exist, the lower the user's accuracy.

User's accuracy (%) = 100 % - error of commission (%)………… (4.2)

4.3. KAPPA COEFFICIENT

The Kappa coefficient was introduced to the remote sensing community in the early 1980s (Congalton and Mead, 1983) and has become a widely used measure for classification accuracy. It was recommended as a standard by Rosenfield and Fitzpatrick-Lins (1986). The kappa coefficient is a measure of overall agreement of a matrix. In contrast to the overall accuracy the ratio of the sum of diagonal values to total number of cell counts in the matrix the Kappa coefficient takes also non-diagonal elements into account (Rosenfield and Fitzpatrick, 1986). Kappa coefficient is a statistical measure of inter-rater reliability (Cohen, 1960). It measures the proportion of agreement after chance agreements have been removed from considerations. It is generally thought to be a more reliable measure than simple percent agreement calculation, since Κ takes into account the agreement occurring by chance.

The equation for the kappa coefficient is given as

$$\hat{K} = \frac{N \sum_{i=1}^{r} X_{ii} - \sum_{i=1}^{r} X_{i+} X_{+i}}{N^2 - \sum_{i=1}^{r} X_{i+} X_{+i}} \text{…………… (4.3)}$$

Where

r = number of rows and columns in error matrix,

N = total number of observations,

X_{ii} = observation in row *i* and column *i*,

X_{i+} = marginal total of row *i*, and

X_{+i} = marginal total of column *i*.

Another formula to find kappa coefficient is

$$\hat{K} = \frac{p_o - p_e}{1 - p_e} \text{…………… …………………………(4.4)}$$

Where

$p_o =$ Accuracy of the observed agreement, $\frac{\sum X_{ii}}{N}$

$p_e =$ Estimate of chance agreement, $\frac{\sum X_{i+} X_{+i}}{N^2}$

A table for interpreting Κ values is given by Landis & Koch (1977). Although it is based on personal opinion and by no means universally accepted, it is presented here (Table 4.2), as many studies refer to it (Altmann, 1991; Kulbach, 1997; Ortiz et al., 1997; Komagata, 2002; Oehmichen, 2007).

Table - 4.2 Interpretation of K-values

Kappa value[%]	Interpretation
<0	Poor agreement
0 to 20	Slight agreement
20 to 40	Fair agreement
40 to 60	Moderate agreement
60 to 80	Substantial agreement
80 to 100	Almost perfect agreement

For example a Kappa coefficient value of 0.67 can be thought of as an indication that an observed classification is 67 percent one resulting from chance.

CHAPTER 5

SIMULATIONS AND RESULTS

In this thesis work, we have considered *synthetic aperture radar* images. The SAR images are classified by using 3 different algorithms, namely Particle Swarm Optimization (PSO), Fuzzy C-Means algorithm (FCM) and K-means algorithm. The performance of these three algorithms is compared using "Confusion Matrix" or error matrix, overall accuracy and Kappa coefficient. The obtained results showed that, among these three algorithms the PSO algorithm gives better classification results over the FCM and K-means classification algorithms.

The fig 5.1.2(a) shows the SAR image courtesy of The Reo Grande River at Albuquerque, New Mexico; which was taken from Sandia National Laboratories SAR imagery. The survey area is part of river, and the primary objective of this survey was to discriminate various objects. The observed image was expected to fall into three classes: river, vegetation and crop. The corresponding PSO classified, FCM classified and K-means classified images are shown in figures 5.1.2(b), 5.1.2(c) and 5.1.2(d) respectively. Each simulation took 100 iterations to get successful results.

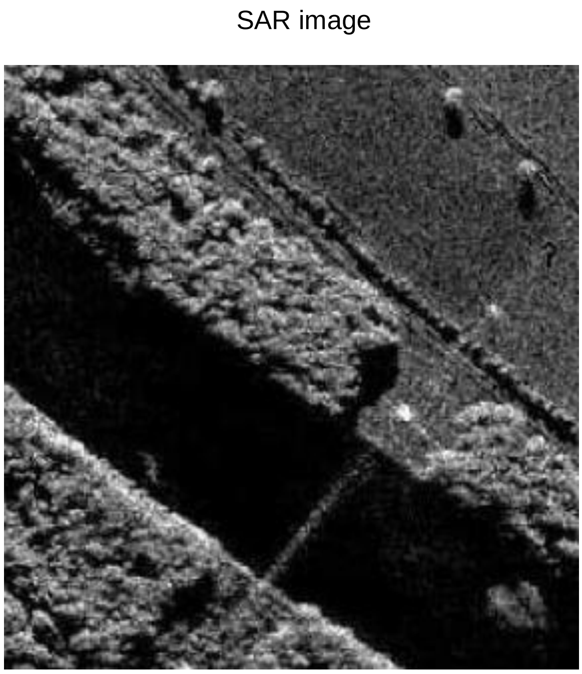
For the classification of SAR image using PSO algorithm, we need the textures for all the existing classes. These textures were shown in figure 5.1.1. The parameters used for the PSO algorithm are Acceleration constants C_1 =0.5, C_2 =0.5 and $W(t) = 0.85$, this $W(t)$ varies with no of iterations.

PSO classes

Vegetation River Crop

Figure 5.1.1.Three different textures of original Reo Grande River SAR image for PSO classification Algorithm.

The cluster centers obtained through PSO algorithm simulation are [111 7 67], which represents the image pixel's gray values. In simulation of FCM algorithm we set the parameters fuzzy factor (m) = 2, error (ε) = 0.01. The cluster centers obtained through simulation are [106 8 60]. The cluster centers obtained through K-means algorithm simulation are [177 2 57].



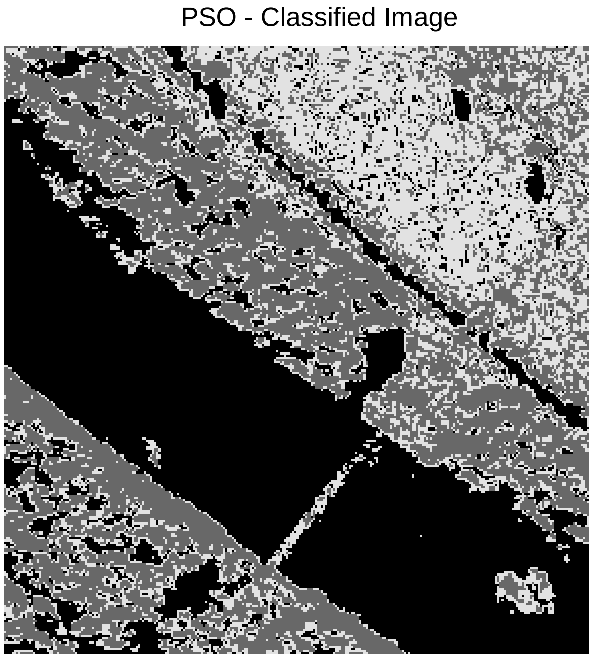
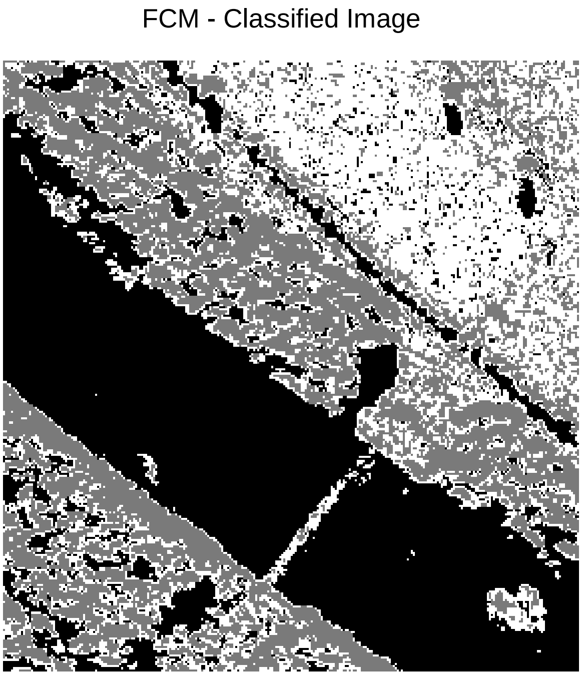


Figure5.1.2 (a) The Reo Grande River SAR Image

Figure 5.1.2(b) The PSO classified Image



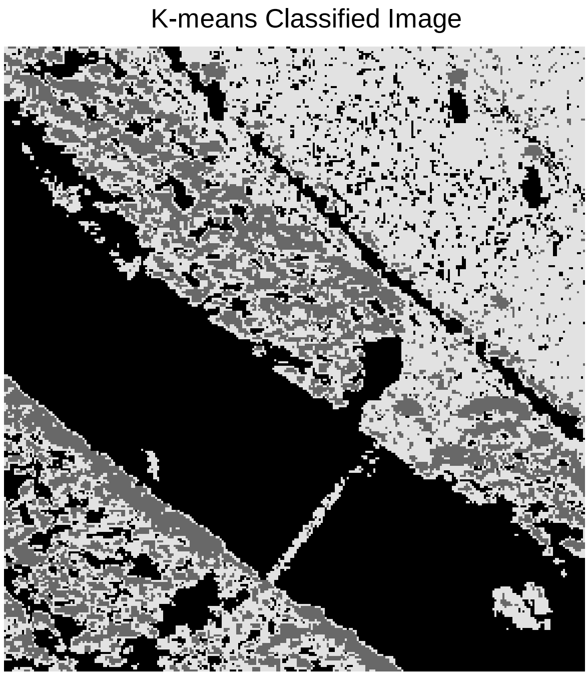


Figure 5.1.2(c) The FCM classified Image

Figure 5.1.2(d) The K-means classified Image

Vegetation River Crop

The results were based on the minimum distance of the image pixels from the cluster centriodes. The image pixel's probability density function (pdf) as a function of pixel's gray level is shown in figure 5.1.3. This figure also represents the classification of the pixel's gray Values based on the above stated minimum distance rule. The pdf for the PSO algorithm, for the FCM algorithm and for the K-means algo rithm are shown in figures 5.1.3(a), 5.1.3(b) and 5.1.3(c) respectively.

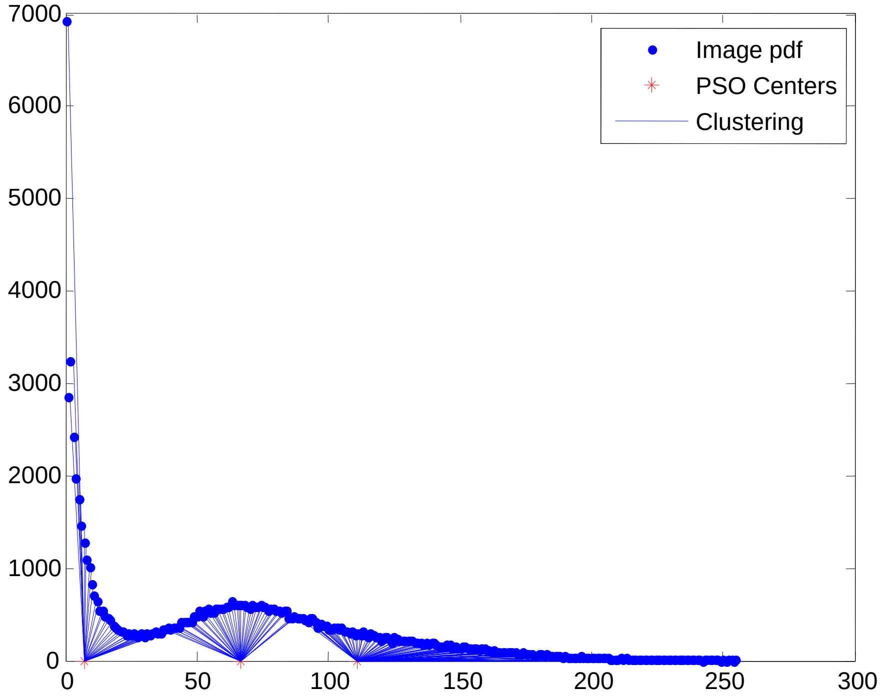


Figure 5.1.3(a) PSO classified Image pdf with cluster centres [7 67 111]

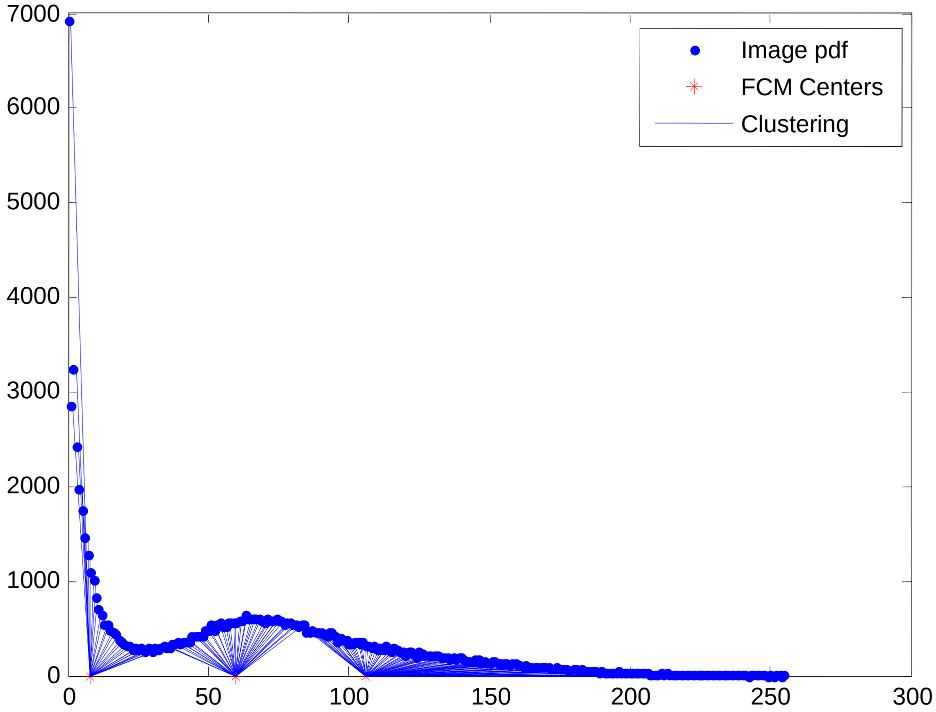


Figure 5.1.3(b) FCM classified Image pdf with cluster centres [8 60 106]

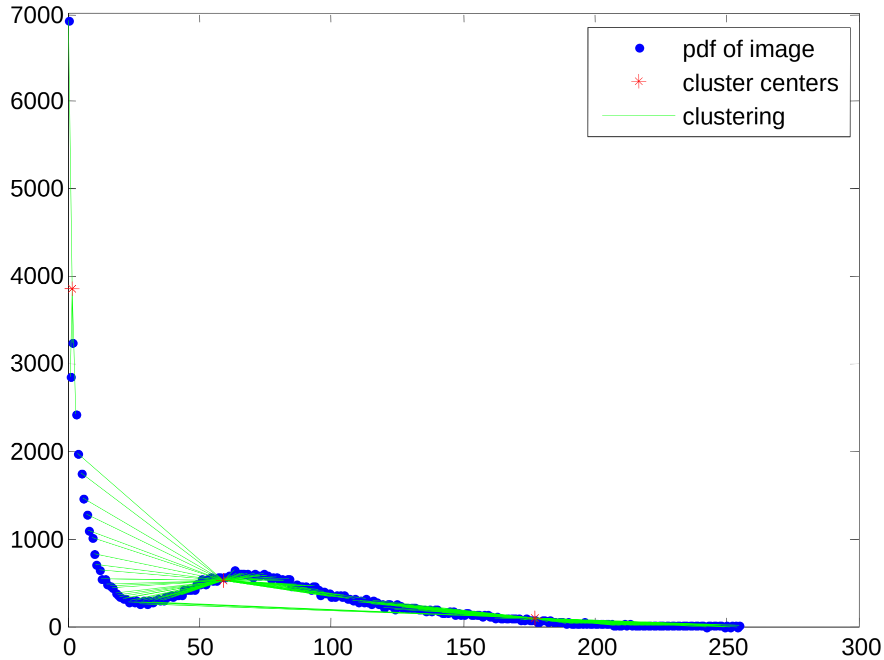


Figure 5.1.3(c) K-means classified Image pdf with cluster centres [2 57 177]

The table 5.1.4(a) shows the Confusion Matrix and the table 5.1.4(b) shows the Accuracy Assessment for the Original SAR image shown in figure 5.1.1(a) w.r.t. all the three classification algorithms.

Table 5.1.4(a) Confusion matrix

REFERENCE DATA

CLASSIFIED DATA

PSO classified image	Vegetation	River	Crop	$\sum$	User's accuracy
Vegetation	70.2	0.6	7.3	78.1	89.88 %
River	9.4	98.2	2.6	110.2	89.11 %
Crop	20.4	1.2	91.1	112.7	80.83 %
$\sum$	100	100	100	--	--
Procedure's accuracy	70.2 %	98.20 %	91.10 %	--	--
FCM classified image	Vegetation	River	Crop	$\sum$	User's accuracy
Vegetation	67.6	2.7	9.2	79.5	85.00 %
River	9.5	96.1	2.5	108.1	88.89%
Crop	22.9	1.2	88.3	112.4	78.55 %
$\sum$	100	100	100	--	--
Procedure's accuracy	67.6 %	96.1 %	88.3 %	--	--
K-means	Vegetation	River	Crop	$\sum$	User's accuracy
Vegetation	62.4	1.0	10.1	73.5	84.89 %
River	10.5	94.0	2.5	107	87.85 %
Crop	27.1	5	87.4	119.5	74.38 %
$\sum$	100	100	100	--	--
Procedure's accuracy	62.4 %	94.0 %	97.4 %	--	--

Table 5.1.4(b) Accuracy Assessment

Classification Technique	Overall accuracy	Kappa coefficient
PSO	86.50 %	0.82
FCM	84.00 %	0.76
K-means	81.26 %	0.71

The fig 5.2.2(a) shows the RADARSAT-1 SAR image of Keweenaw Peninsula-Marquette region of Lake Superior. The resolution of the SAR image is about 50 m. The survey area is part of Ice, and the primary objective of this survey was to discriminate various objects. The observed image was expected to fall into three classes: Ice, Water and Ground. The corresponding PSO classified, FCM classified and K-means classified images are shown in figures 5.2.2(b), 5.2.2(c) and 5.2.2(d) respectively. Each simulation took 100 iterations to get successful results.

For the classification of SAR image using PSO algorithm, we need the textures for all the existing classes. These textures were shown in figure 5.2.1. The parameters used for the PSO algorithm are Acceleration constants C_1 =0.5, C_2 =0.5 and, $W(t) = 0.77$ this $W(t)$ varies with no of iterations.

PSO classes

Ground Water Ice

Figure 5.2.1.Three different textures of original RADARSAT-1 SAR image for PSO classification algorithm.

The cluster centers obtained through PSO algorithm simulation are [40 83 186], which represents the image pixel's gray values. In simulation of FCM algorithm we set the parameters fuzzy factor (m) = 2, error (ε) = 0.01. The cluster centers obtained through simulation are [45 85 193]. The cluster centers obtained through K-means algorithm simulation are [68 188 189].

SAR image

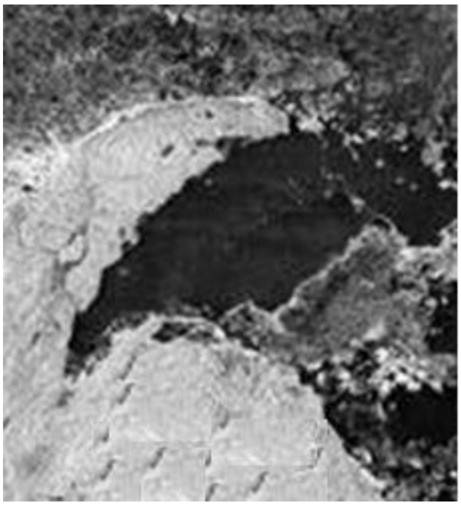


Figure 5.2.2(a) RADARSAT-1 SAR image

PSO - Classified Image

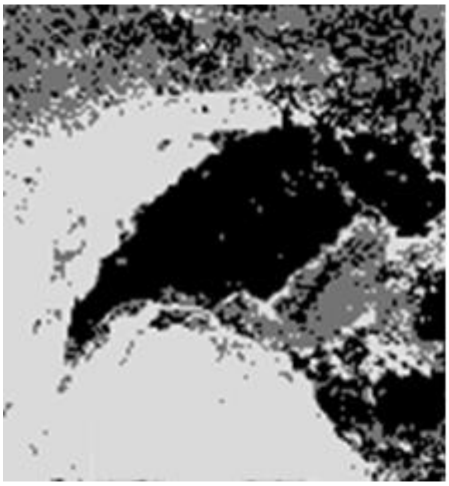


Figure 5.2.2(b) The PSO classified Image

FCM- Classified Image

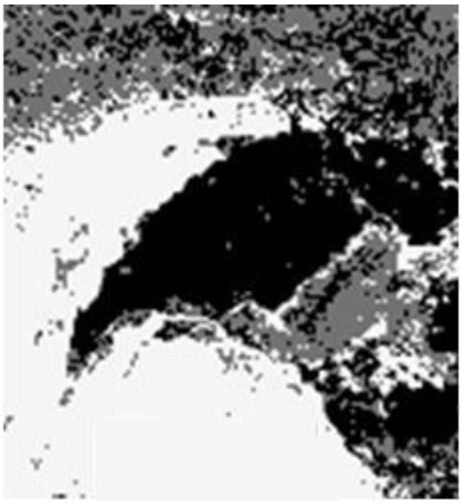


Figure 5.2.2 (c) The FCM classified Image

K-means Classified Image

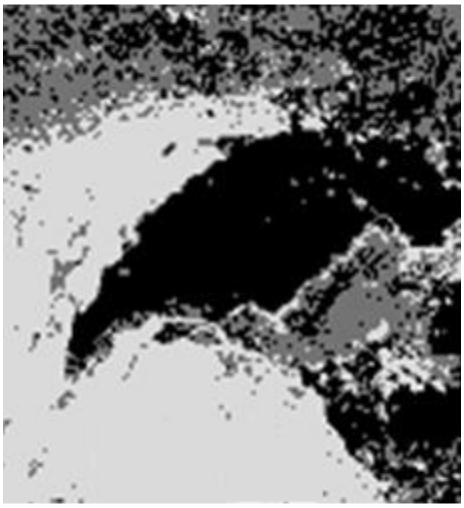


Figure 5.2.2(d) The K-means classified Image

Ground Water Ice

The image pixel's probability density function (pdf) as a function of pixel's gray level is shown in figure 5.2.3. This figure also represents the classification of the pixel's gray values based on the above stated minimum distance rule. The pdf for the PSO algorithm, for the FCM algorithm and for the K-means algorithm are shown in figures 5.2.3(a), 5.2.3(b) and 5.2.3(c) respectively.

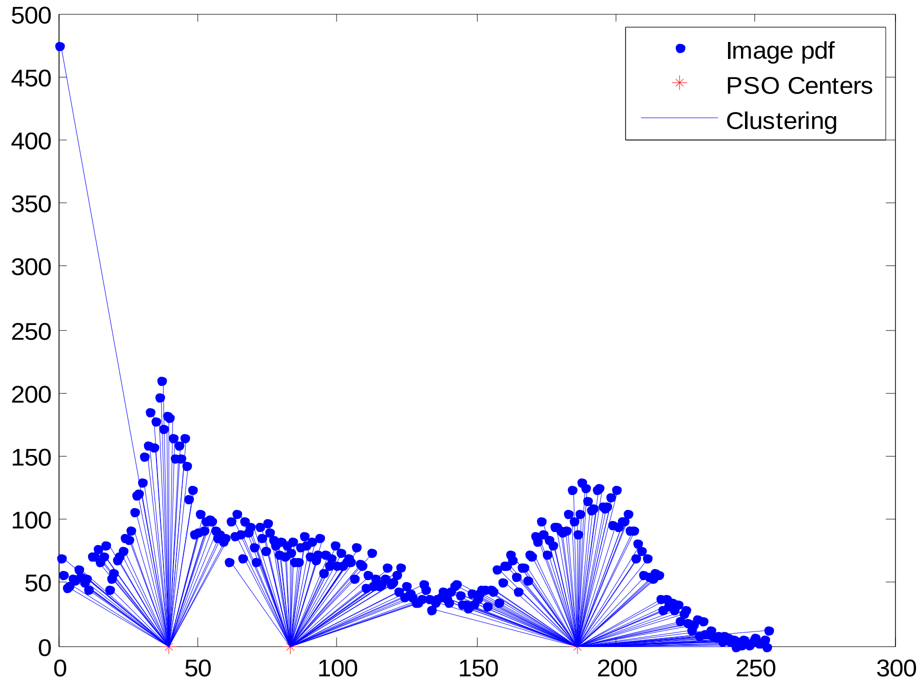


Figure 5.2.3(a) PSO classified Image pdf with cluster centers [40 83 186]

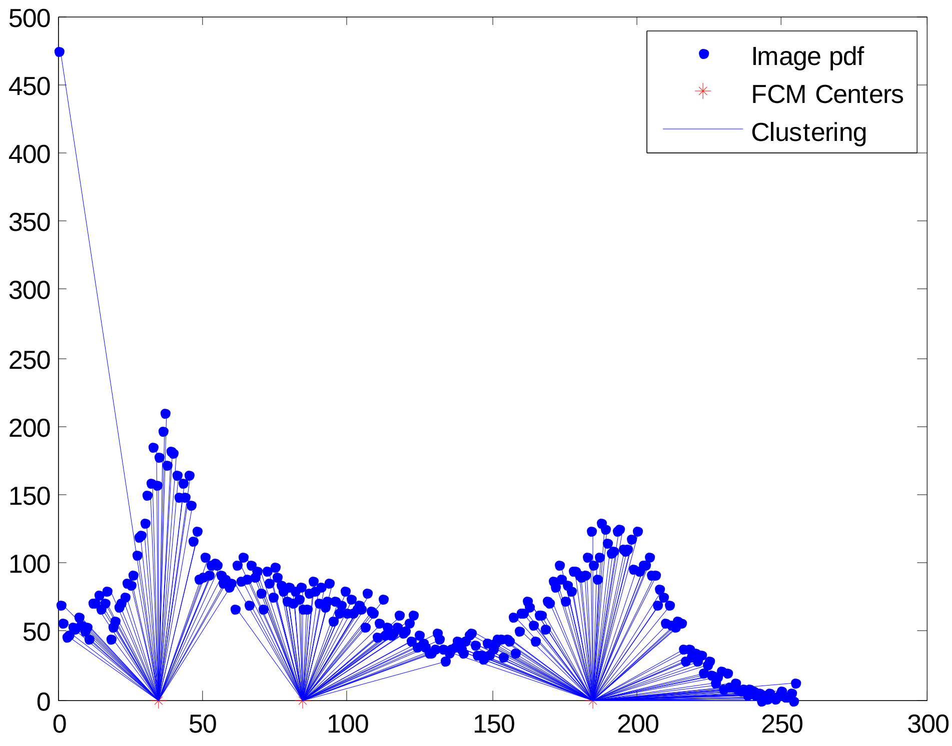


Figure 5.2.3(b) FCM classified Image pdf with cluster centers [45 85 193]

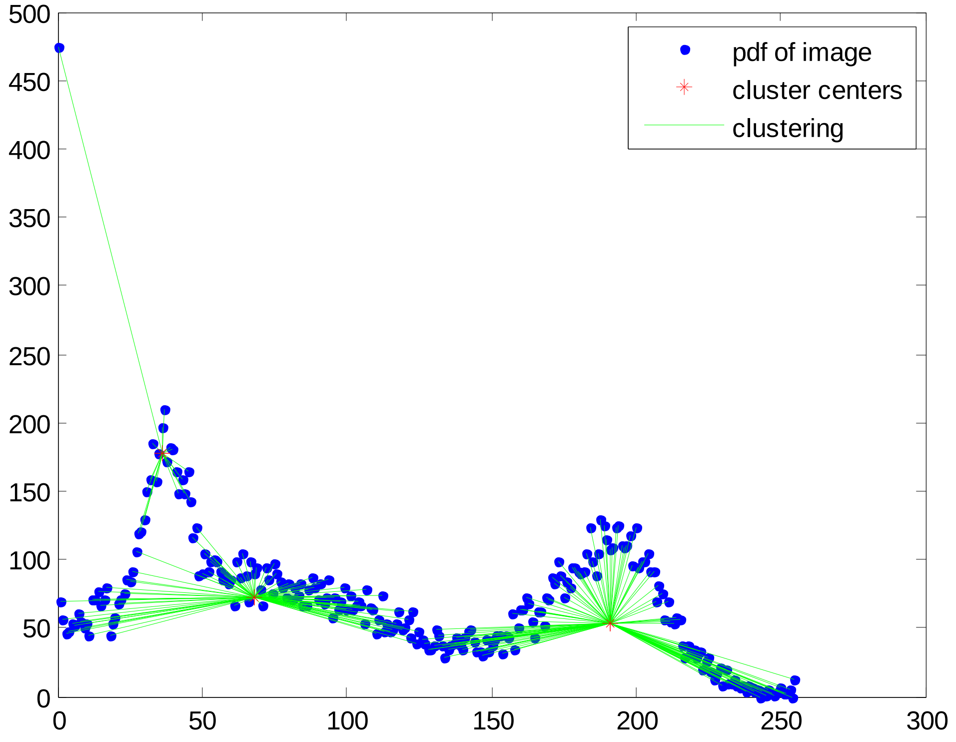


Figure 5.2.3(c) K-means classified Image pdf with cluster centers [36 68 191].

The table 5.2.4(a) shows the Confusion Matrix and the table 5.2.4(b) shows the Accuracy Assessment for the RADARSAT-1 SAR image shown in figure 5.2.1(a) w.r.t. all the three classification algorithms.

Table 5.2.4(a) Confusion matrix

REFERENCE DATA

C
L
A
S
S
I
F
I
E
D

D
A
T
A

PSO classified image	Ice	Water	Ground	∑	User's accuracy
Ice	95.2	4.7	7.3	107.2	88.80 %
Water	1.2	86.6	11.4	99.2	93.92 %
Ground	3.6	8.7	81.3	93.6	86.85 %
∑	100	100	100	--	--
Procedure's accuracy	95.2 %	86.6 %	81.3 %	--	--
FCM classified image	Ice	Water	Ground	∑	User's accuracy
Ice	92.4	6.7	8.2	107.3	86.39 %
Water	3.3	83.5	12.7	99.5	83.91 %
Ground	4.3	9.8	79.1	93.2	84.87%
∑	100	100	100	--	--
Procedure's accuracy	92.4 %	83.5 %	79.1 %	--	--
K-means	Ice	Water	Ground	∑	User's accuracy
Ice	90.2	5.6	7.2	103	87.66 %
Water	3.5	85.3	15.6	104.4	81.70 %
Ground	6.3	9.1	77.2	92.6	83.36 %
∑	100	100	100	--	--
Procedure's accuracy	90.2 %	85.3 %	77.2 %	--	--

Table 5.2.4(b) Accuracy Assessment

Technique	Overall accuracy	Kappa coefficient
PSO	87.70 %	0.81
FCM	85.00 %	0.77
K-means	84.23 %	0.76

The fig 5.3.2(a) shows the L-band San Francisco SAR image. The survey area is part of Ocean, and the primary objective of this survey was to discriminate various objects. The observed image was expected to fall into three classes: Ocean, Forest and Urban. The corresponding PSO classified, FCM classified and K-means classified images are shown in figures 5.3.2(b), 5.3.2(c) and 5.3.2(d) respectively. Each simulation took 100 iterations to get successful results.

For the classification of SAR image using PSO algorithm, we need the textures for all the existing classes. These textures were shown in figure 5.3.1. The parameters used for the PSO algorithm are Acceleration constants C_1 =0.5, C_2 =0.5 and, $W(t) = 0.79$ this $W(t)$ varies with no of iterations.

PSO classes

Ocean Forest Urban

Figure 5.3.1.Three different textures of original L-band San Francisco SAR image for PSO classification algorithm.

The cluster centers obtained through PSO algorithm simulation are [30 130 183], which represents the image pixel's gray values. In simulation of FCM algorithm we set the parameters fuzzy factor (m) = 2, error (ε) = 0.01. The cluster centers obtained through simulation are C= [25 126 187]. The cluster centers obtained through K-means algorithm simulation are [83 127 232].

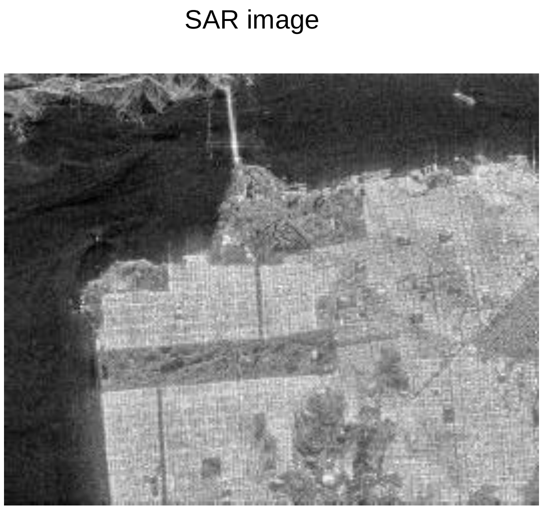


Figure 5.3.2(a) San Francisco SAR image

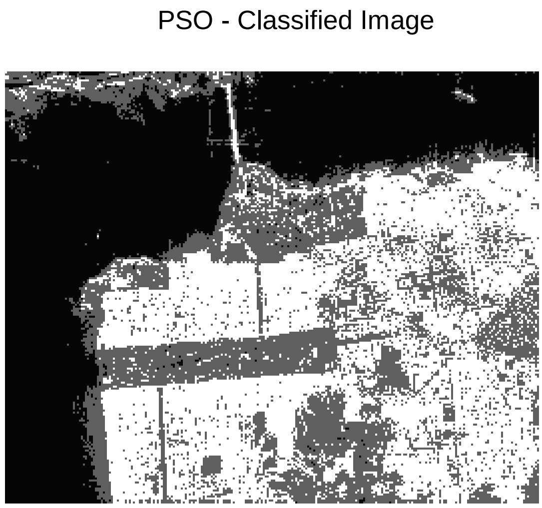


Figure 5.3.2(b) The PSO classified Image

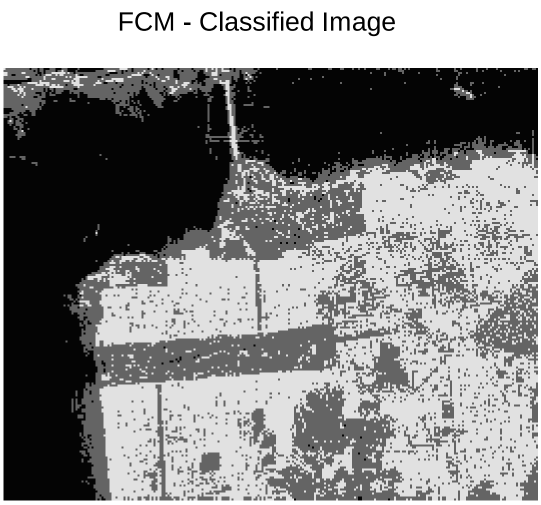


Figure 5.3.2(c) The FCM classified Image

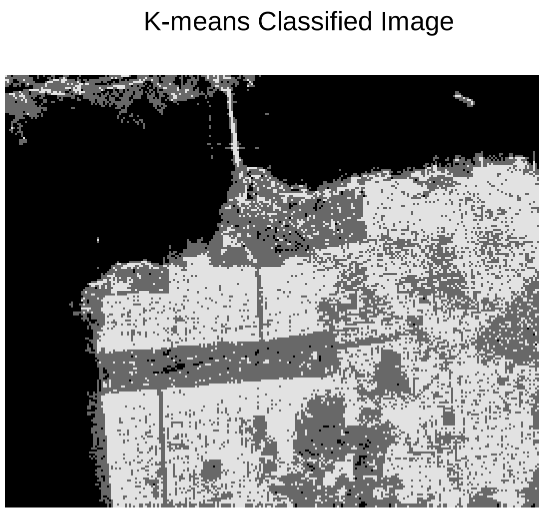


Figure5.3.2 (d) The K-means classified Image

The image pixel’s probability density function (pdf) as a function of pixel’s gray level is shown in figure 5.3.3. This figure also represents the classification of the pixel’s gray values based on the above stated minimum distance rule. The pdf for the PSO algorithm, for the FCM algorithm and for the K-means algorithm are shown in figures 5.3.3(a), 5.3.3(b) and 5.3.3(c) respectively.

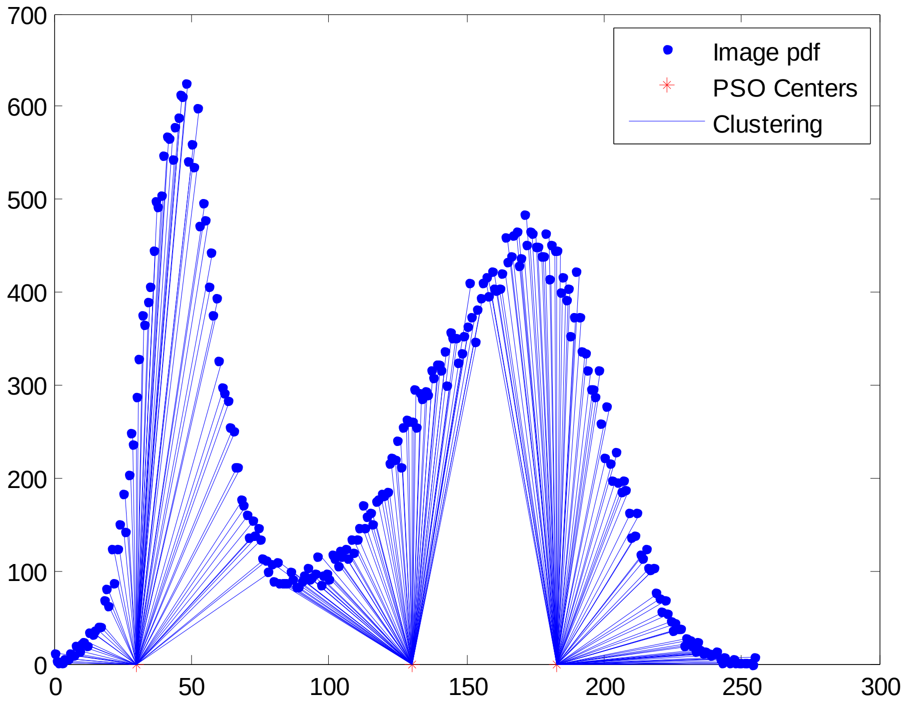


Figure 5.3.3(a) PSO classified Image pdf with cluster centers [30 130 183]

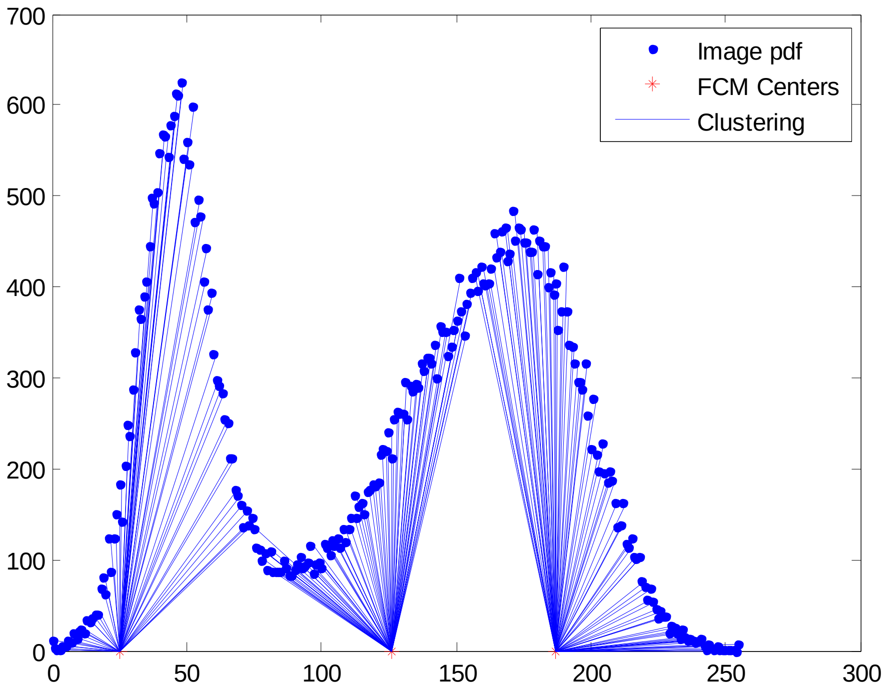


Figure 5.3.3(b) FCM classified Image pdf with cluster centers [25 126 187]

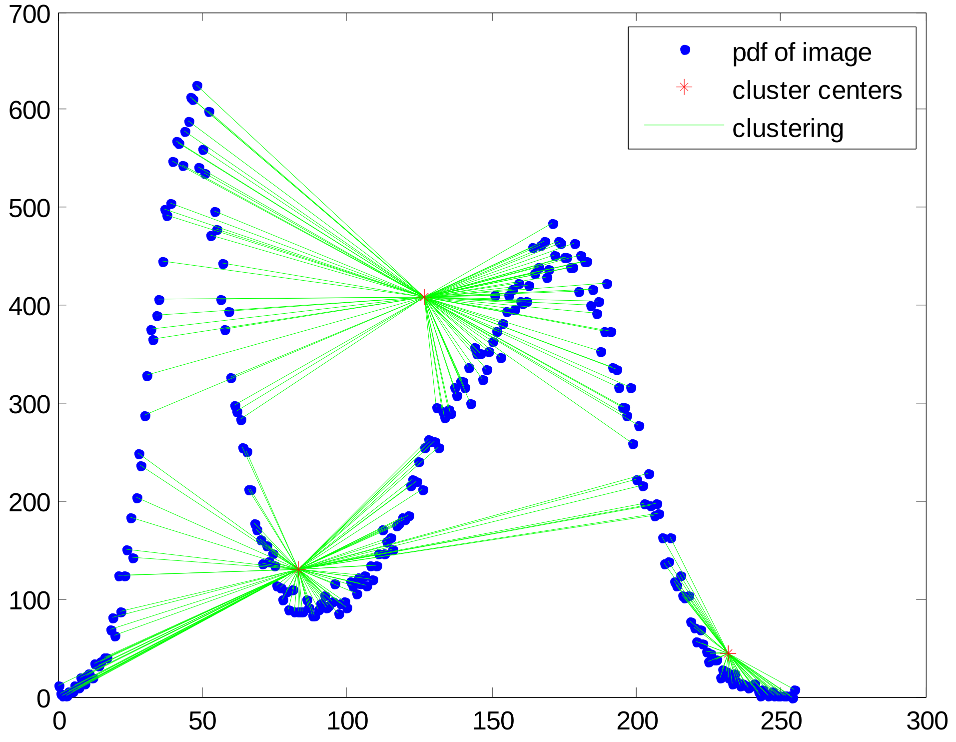


Figure 5.3.3(c) K-means classified Image pdf with cluster centers [83 127 232]

The table 5.3.4(a) shows the Confusion Matrix and the table 5.3.4(b) shows the Accuracy Assessment for the San Francisco SAR image shown in figure 5.3.1(a) w.r.t. all the three classification algorithms.

Table 5.3.4(a) Confusion matrix

REFERENCE DATA

CLASSIFIED DAT

PSO classified image	Ocean	Forest	Urban	$\sum$	User's accuracy
Ocean	91.2	1.8	1.3	94.3	96.71 %
Forest	6.6	86.3	14.4	107.3	80.42 %
Urban	2.2	11.9	84.3	98.4	85.67 %
$\sum$	100	100	100	--	--
Procedure's accuracy	91.2 %	86.3 %	84.3 %	--	--
FCM classified image	Ocean	Forest	Urban	$\sum$	User's accuracy
Ocean	89.4	2.1	1.4	92.9	96.23 %
Forest	7.3	83.1	17.2	107.6	77.23 %
Urban	3.3	14.8	81.4	99.5	81.80%
$\sum$	100	100	100	--	--
Procedure's accuracy	89.4 %	83.1 %	81.4 %	--	--
K-means	Ocean	Forest	Urban	$\sum$	User's accuracy
Ocean	92.6	6.2	1.6	100.4	92.23%
Forest	4.5	78.6	19.7	102.8	76.45 %
Urban	2.9	15.2	78.7	96.8	81.30 %
$\sum$	100	100	100	--	--
Procedure's accuracy	92.6 %	78.6 %	78.7 %	--	--

Table 5.3.4(b) Accuracy Assessment

Technique	Overall accuracy	Kappa coefficient
PSO	87.26 %	0.80
FCM	84.63 %	0.76
K-means	83.30 %	0.74

CHAPTER 6

CONCLUSION

6.1 CONCLUSIONS

This chapter summarizes and concludes the investigation of SAR image classification presented in this thesis. It emphasizes the main points of the theoretic and practical work performed during this project and presents conclusions that can be drawn from the results. Some image classification methods have been studied. All are given acceptable results.

In this thesis a novel algorithm based on the Particle Swarm Optimization, was designed for SAR images classification. The new algorithm is successfully applied for classification of SAR images. The experimental results consistently show that the proposed algorithm has high classification precision. When compared with other two classifiers, K-means, and FCM, the average performance of PSO is better than them. The performance is evaluated by accuracy assessment.

In terms of image classification accuracy evaluation, attention was mainly focused on subjective methods of evaluation. Confusion matrix, overall accuracy and Kappa coefficient are the main considerations in organizing and running subjective tests for method of image classification accuracy evaluation.

The PSO clustering algorithm is used to obtain the proper centroids of clusters for minimizing the intra-cluster distance as well as maximizing the distance between clusters. The effectiveness of PSO algorithm was evaluated by accuracy assessment. We achieved more accuracy with PSO because it is a global searching technique. The performance of PSO technique is found to be satisfactory and the performance of outperformed FCM and K-means technique. The classification results are validated with various SAR images.

6.2 FUTURE WORK

Classification of SAR images using PSO technique requires training sample of every region in the image. So the number of classes is assumed to be known. Hence this problem can be considered to semi-supervised. Future work can be extended by considering the classification problem to be completely unsupervised where the no. of classes are unknown this problem is both pursuing and computational burden is to be considered along with other subjective tests for performance measurement.

REFERENCES

[1] C. W. Sherwin, J. P. Ruina, and R. D. Rawcliffe, "Some early developments in synthetic aperture radar systems," IRE *Trans .Mil.* Electron. Vol. MIL-6, pp. 111-1 15, Apr. 1962.

[2] Gao Lan, Zhan Jianqiang, Lu Ling, Song Wenwu**,** "Segmentation of SAR image in electromagnetic environment based on fractal theory" Asia-Pacific Conference on Environmental Electromagnetics, CEEM' NOV 4-7,2003 Hangzhou, CHINA.

[3] Saevarsson, B.B, Sveinsson, J.R, Benediktsson J.A, "Combined Wavelet and Curvelet denoising of SAR Images", IEEE Transactions on Geosciences and Remote Sensing, Vol6, pp. 4235-4238, Sept 2004.

[4] Zheng-Wen Xu, JianWu and Zhen-Sen Wu, "A survey of ionospheric effects on space-based radar" Institute of Physics Publishing, Waves Random Media **14** (2004) S189–S273.[5] Lee J S, Grunes M R, Kwok R. "Classification of multi-look polarimetric SAR imagery based on complex Wishart distribution", Int. J. Remote Sensing, 1994, **15**(11): 2299-2311.

[6] Van Zyl J J. "Unsupervised classification of scattering behavior using radar polarimetry data",*IEEE Trans. Geosci. Remote Sensing*, 1989, **27**(1): 36-45.

[7] Bischof H, Schneider W, Pinz A J. "Multispectral classification of landsat-images using neural networks", IEEE Trans. Geosci. Remote Sensing, 1992, **30**(3): 482-490.

[8] Chen C T, Chen K S, Lee J S. "The use of fully polarimetric information for the fuzzy neural classification of SAR images", IEEE Trans. Geosci. Remote Sensing, 2003, **41**(9 Part I): 2089-2100.

[9] Du L, Lee J S. "Fuzzy classification of earth terrain covers using complex polarimetric SAR data", International Journal of Remote Sensing, 1996, **17**(4): 809-826.

[10] Fukuda S, Hirosawa H. "A wavelet-based texture feature set applied to classification of multi frequency polarimetric SAR images". *IEEE Trans. Geosci. Remote Sensing,* 1999, **37**(5): 2282-2286.

[11] Céline Tison, Jean-Marie Nicolas, Florence Tupin, and Henri Maître."A new Statistical Model for Markovian Classification of Urban Areas in High-Resolution SAR Images" IEEE Trans. Geoscience and Remote sensing, Vol. 42, No. 10, October 2004.

[12] Lan Gao, Feng pan, XiaoQuan Li.A "New Fuzzy Unsupervised Classification Method for SAR Images" IEEE Trans.2006.

[13] H. Frigui and R. Krishnapuram, "A robust competitive clustering algorithm with applications in computer vision," IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 21, no. 5, pp. 450–465, 1999.

[14] J. Zhang Y. Leung and Z. Xu, “Clustering by space-space filtering,” IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 22, no. 12, pp. 1396–1410, 2000.
[15] Russ C.Eberhart, J.kennedy, “A new optimizer using Particle Swarm Theory”, In proceedings of the Sixth International Symposium on Micro Machine and Human Science, Pages 39-43, Nagoya, Japan, 1995.
[16] J. Kennedy, R. C. Eberhart, "Particle swarm optimization", Proc. IEEE Int. Conf Neural Networks, vol. 4, Perth, Australia, Dec. 1995, pp. 1942-1948.
[17] J. Kennedy, R. C. Eberhart, “Swarm Intelligence”, Morgan Kaufman, San Mateo, Ca, 2001.
[18] Y.Shi, Russ C.Eberhart, “A Modified Particle Swarm Optimizer”, IEEE International Conference of Evolutionary Computation, Anchorage, Alaska, May 1998.
[19] A. Salman M. Omran and A. Engelbrecht, “Image classification using particle swarm optimization,” in Conference on Simulated Evolution and Learning, Singapore, 2002, vol. 1, pp. 370–374.
[20] Xiaohui Cui, Thomas E. Potok, Paul Palathingal, “Document Clustering using Particle Swarm Optimization”, Applied Software Engineering Research Group Computational Sciences and Engineering Division Oak Ridge National Laboratory.