T.R.
ONDOKUZ MAYIS UNIVERSITY
INSTITUTE OF GRADUATE STUDIES
DEPARTMENT OF NANOSCIENCE AND NANOTECHNOLOGY

SEM IMAGE NANOMATERIALS ANALYSIS AND CHARACTERIZATION USING SEGMENTATION ALGORITHMS

Master Thesis

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Supervisor

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Assoc. Prof. Dr. Nurettin ŞENYER

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ÖZET

SEGMENTASYON ALGORITMALARINI KULLANARAK SEM GÖRÜNTÜ NANOMALZEME ANALIZI VE KARAKTERIZASYONU

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Nanobilim ve Nanoteknoloji Anabilim Dalı
Yüksek Lisans, Nisan/2022
Danışman: Doç. Dr. Özgür DEMİRCAN

Nano-görüntü işleme, nanoteknoloji uygulamalarının en kapsamlı olmayan listesinden biri olarak kabul edilir. Atomik kuvvet mikroskobu (AFM) ve yüksek çözünürlüklü taramalı elektron mikroskobu (SEM) gibi mikroskopi teknolojileri, nanoyapıları görselleştirmek ve karakterize etmek için kullanmak için idealdir. Nano ölçekli işlemede kesin bir adım olarak kabul edilen görüntü segmentasyonu. Bölütleme elde etmek için farklı yöntemler vardır, Nano ölçekli görüntü işlemede istatistiksel yaklaşımlar olarak bilinen birçok başka yöntem kullanılır. Genel olarak, optimum eşiği bulmak için bir dizi denklem Gaussian dağılımı gibi yöntemlerle çözülebilir.

Bu çalışmada, beklenti-maksimizasyon (EM), k-ortalamalar, histogram ve eşik yöntemleri gibi çeşitli yöntemler kullanılan Nanomalzemeler karakterizasyon çıkarmak için Nanomalzeme görüntü bölütleme yöntemleri değerlendirilir. Bu yöntemler, yaklaşımı istatistiksel kullanarak optimal eşiği belirlenecek sağlar.

Bu tezde, SEM nanomalzemelerinin görüntü özelliklerini incelemek için bahsedilen yöntemler kullanılmıştır. Tüm bu teknolojilerin karşılaştırmaları, gerçek nanomalzemelerin görüntüleri için kapsamlı bir şekilde incelenmiş ve simüle edilmiştir. SEM tarafından elde edilen görüntüler, son görüntü analizi için yeterlidir.

Çalışmadan elde edilen analiz sonuçları nanoteknoloji alanında bilim insanlarına yardımcı olacaktır. Önerilen çalışmalar Nano-görüntü malzemelerinin segmentasyonunudur analiz edecek ve Nano-malzeme çapının uzunluğunu, yönünü ve yoğunluğunu, Nano-görüntü işleme teknikleri için histogram ölçecektir.

Anahtar Kelimeler: Nano-malzeme, Nanoteknoloji, Görüntü Bölümleme, SEM, EM K-ortalamalar, Nano-ölçek.

ABSTRACT

SEM IMAGE NONMATERIALS ANALYSIS AND CHARACTERIZATION
USING SEGMENTATION ALGORITHMS
Fadya Ibrahim Nayyef AL-MASHHADANI
Ondokuz Mayıs University
Institute of Graduate Studies
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Master Thesis, April /2022
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Nano-image processing is considered as one of the most non-exhaustive list of nanotechnology applications. The microscopy technologies such as atomic force microscopy (AFM) and high-resolution scanning electron microscopy (SEM) and ideal to use them in to visualize and characterize of the nanostructures. Image segmentation considered as a definitive step in Nano-scale processing. There are different methods to attain segmentation. Many other methods are used in the Nano-scale image processing, known as statistical approximations. One way is the statistical approach. Generally, a set of equations can be solved by methods like Gaussian distribution to find the optimum threshold.

In this study, Nano-material image segmentation methods will be evaluated to extract the Nano-material characterization by using different kinds of methods, i.e. expectation-maximization (EM), k-means, histogram, and threshold methods. These methods enable to define the optimal threshold by using the statistical approach.

In this thesis, the mentioned methods are used to study the characteristics of SEM Nano-materials image. The Comparisons of all these techniques are intensively studied and simulated with real Nano-material images. The images obtained by SEM are sufficient to analyze recent images.

The analysis results obtained from the study will help the scientist in the field of nanotechnology. The proposed studies will analysis the segmentation of the Nano-image materials and measure the length, orientation and density of the Nano- materials diameter, histogram for the Nano-image processing techniques.

Keywords: Nano-material, Nanotechnology, Image Segmentation, K-means, EM, SEM, Nano-scale.

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Also, I must thank my colleague Dr. Elmustafa Sayed ALİ for his helps in all matters of writing the thesis.

Finally, I dedicate this work and all my future endeavors to my family. To my father for his faith in my capabilities, for his strength patience while fighting the threatens to his health and for his continuous support me over my life. To my mother, who give me the greatest love, support and courage, for her endless care and love for his family, were she exercised great and endless patience. To my sister and my brothers who always and forever I hope they become better than me.

Fadya Ibrahim Nayyef AL-MASSHADANI

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ABBREVIATION OF TERMS

SEM Scanning Electron Microscopy

AFM Atomic Force Microscopy

EM Expectation-Maximization

MSE Mean Square Error

PSNR Peak Signal to Noise Ratio

EBSD Electron Backscatter Diffraction

SRG Seeded Region Growth

GMM Gaussian Mixture Model

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1. INTRODUCTION

The mission of image analyzing becomes monumental when one tries to understand, characterize and extract relevant information from an image. The non-exhaustive list of applications where image processing is needed are in medical, biological purposes, multimedia, photo and video, security, surveillance, robotic, biometrics, and remote sensing (Costa, 2004). More recently, image analysis has been used in the field of nanotechnology (Chuklanov, 2006). Nanotechnology is a field of applied science aimed at producing and using engineered materials, which has in atomic structure or molecular scale (Elizabeth et al., 2016). This kind of material is known as nanoparticles, which has at least one dimension less than 100 nanometers. The technologies like atomic force microscopy (AFM) and high-resolution scanning electron microscopy (SEM) are used to characterize the nanoparticles materials (Poletti. Et al., 2003). These technologies enable to capture nanoparticles images in order to widely analysis and processing to extensively analyzed and processed for the features and information about the nanoparticles in quality and quantity term, in addition to extract the physical properties including length ,size, surface texture, density morphology and roughness.

Although, images obtained by SEM and AFM are suitable for the analysis of the above properties. This because, the images are abstract, they cannot be analyzed in the original image format. The original images must be subjected to many image-preprocessing techniques to enable the researcher's study to search process and get the optimal information (Chuklanov, 2006; Spisz. T.S. et al., 1998).

The aim of pre-processing steps to improve contrast, restore, background subtraction, and compression. Once the image has been pre-processed, the most important next step is to make image segmentation. Image segmentation is a technique enables to extract the associated similar image features based on intensity, color and texture (Cheng. et al., 2003; Zhang H. et al., 2008).

The following parts, the segmentation threshold intensity (Nagarajan, 2003), edge segmentation and region segmentation (Rosin, 2001) classify the segmentation techniques. These thresholds can provide a simple and convenient process to execute segmentation based on the different intensity of the image in the foreground and background regions (Wani. et al., 1994).These techniques help to obtain an image segmentation result in the form of a group of segments containing the full image, or a

collection of features extracted from the image. Whereas, all the pixels are attached to an area based on some computed feature or characteristic.

1.1. Background and Motivation

In recent years, there are so many image thresholds algorithms have been developed (Sahoo. P.K. et al., 1988), and none of them perform well under all conditions, because most of them are based on certain conditions and works only under some assumptions. These methods fail when they are applied to SEM or AFM images of nanomaterials because the images are fuzzy and abstract (Costa, 2004). One example of such problems is that nano-image captured by SEM has a poor vision in separating the top view from the stem region (Wani et al., 1994; Anandan. V. et al., 2006), making it difficult to separate the foreground and background regions (Wani et al.. 1994). This hinders the researchers from further processing of their nanomaterials images, forcing them to do such processes like measuring the density, length and orientation of the nanomaterials manually. This is one of the special cases of threshold methods.

In the literature, so many global image threshold methods present are either based on parametric or nonparametric approaches (Chan et al., 1998; Li. C.H. et al., 1993; Sund et al., 2003). Therefore, it is very clear that a good threshold method is required. Although Gaussian distribution is one of the best-proven methods among the best minimum methods (Otsu, 1979; Ridler et al., 1978), there are some serious drawbacks. The performance degrades when the initial parameters are random and the prior probabilities are unbalanced (Ridler et al., 1978; Kittler et al., 1986; Trussell, 1979). In order to address these drawbacks and to find the best suitable method for threshold the nonmaterial images.

Image clustering approach is a well-known method used for segmenting nanoscale images. The features extracted for the image are well combined into different groups according to each image category. In this work, the study will evaluate various statistical algorithms like Expectation-Maximization (EM), k-means and a combination of EM, and k-means to make segmentation for dataset of nanomaterials images. In addition, investigate on the novel concept of obtaining the threshold value from minimum distance method, which is extensively used in statistics.

1.2. Statistical Segmentation Methods

Images are one of the most important means of conveying information, so we need to understand images and extract information from them so that information can be used in other tasks, and it is an important aspect of machine learning. One of the important first steps in understanding images is dividing the image and knowing different things about it. In some cases, as in the case of AFM and SEM images, when an image with a number of different objects is considered, some can be easily separated from one another and others together. In this case, discovering its statistical distributions is a difficult task. Each of the different objects is a separate identity and distinguishes each statistical distribution model. This scenario is referred to as the mixture model.

There are different ways to estimate the mixture model. One of these methods is to assume that each pixel is a member of a distribution model. Then the appropriate parameters for the model are estimated. Once the parameters are obtained, then using an appropriate distribution formula, the pixels are classified. To achieve this consideration, many statistical approaches can be used to fit the mixture model to observed data namely k-Means, EM, minimum distance, the Normalized cuts, etc.

1.3. The K-means Clustering Algorithm

The K-mean technique is the most one widely applied algorithms in clustering process. The means algorithm categorizes a given input data set into (k) groups based on specific measurements and at dedicated distances in the image. This algorithm is considered the most common and widely used in image analysis, statistical data mining, neural network applications, and biometric information classification. The k-means algorithm is also known more commonly because it is characterized by its speed and ease in the process of segmenting images.

The algorithm gives the best performance when the number of groups is small due to its high sensitivity to data sets. Increasing the data in the groups to reach up to 100,000 helps greatly increases the performance of the algorithm significantly. The k-means algorithm is the most one widely studied algorithms, as it is considered as one of the simplest unsupervised learning algorithms that classifies the input data points

into categories based on the intrinsic distance between them and each other. The means algorithm for the characterization of nanomaterials can be defined as follows:

- Reading the nano-materials SEM image and then converting it in 3D or 2D image.
- Suppose the number of clusters is k.
- Suppose randomly k locations of cluster centers.
- Determine which center is closest to each data point given the characteristics and cluster group numbers.
- Find the center of gravity of each cluster and move the center to that location.
- Repeat until convergence.
- Display the resulting images with histograms.

The k-means initial aggregation must be done based on some reasonable assumptions, because the initial aggregation will largely determine the algorithm. The number of (K) clusters must be determined initially. Objective function J of k-means can be calculated as follows,

$$J = \sum_{j=1}^{k} \quad \sum_{i=1}^{n} \quad \| x_i^{(j)} c_j \|^2 \qquad \textbf{(1.1)}$$

Where, k and n are represent the number of cluster and number of cases respectively. $x_i^{(j)}$ is denoted for case i. c_j is for centroid for cluster j.The term $\| x_i^{(j)} c_j \|^2$ is denoted for distance function.

During the process of k-means, the processing is very sensitive to initial conditions, which must be appropriated. This because various initial conditions will manufacture different results that ultimately will impact the process of algorithm.

1.4. The EM Algorithm

The expectation maximization (EM) algorithm extracts maximum probability estimates for model parameters in the event that there are missing data, part of it is missing, or there are latent variables. This algorithm expresses that, it is a method depends on the process of iteration to approximate the maximum probability function, where it is possible to estimate the probability and obtain a flow model for a set of data. However, it is affected in the case of groups containing incomplete data.

Other complex EM algorithms have been developed that can find model parameters in the absence of some data, picking random values for missing data points

and then making estimated assumptions to arrive at a second set of data. The new set is used to create the best estimate for the next set, until obtained a suitable convergence for example; consider a general like the observed data denoted by(a), and the set of unknown parameters θ. Let us assume some parameters initially as p (θ).Then a posteriori probability function is given by p (θ/a). This is proportional to parameter p (a/θ) p (θ). If there is access to some other data b, then it is easy to maximize p (a,b/θ) p (θ), where p (a,b/θ) is related to p (a/θ) through marginalization (Figueiredo, 2004).

$$p(a/\theta) = \int p(b,a/\theta)\, db \qquad \textbf{(1.2)}$$

EM is an iterative procedure between the expectation and maximization step which converges to a local maximum of the marginal a posteriori probability function p (θ/a) =p (a/θ) p (θ) without calculating the marginal likelihood p (θ/a). Therefore, EM estimates the probability that the data is present in a certain cluster.

The main drawback of EM is the initial parameters because EM is more sensitive to initial parameters. Therefore, the initial parameters should always be given a reasonable value. In order to address this problem in EM as well as to increase its stability and capacity, we will use k-means results as basics and apply EM. This is expected to show us some good results (Korting T.S. et al., 2007).

1.5. Materials and methods

A. Nano-materials Images Dataset

The nano-materials dataset, which will be studied, are a comprised of many SEM images of powdered materials and descriptions of the corresponding 3D structures. The images used were created from an open source computer graphics suite using Blender. The data set used assumes that the powders consist of spherical particles with randomly extracted dimensions. The following images in figure 1show a sample of the nano-materials dataset (Elizabeth et al., 2016).

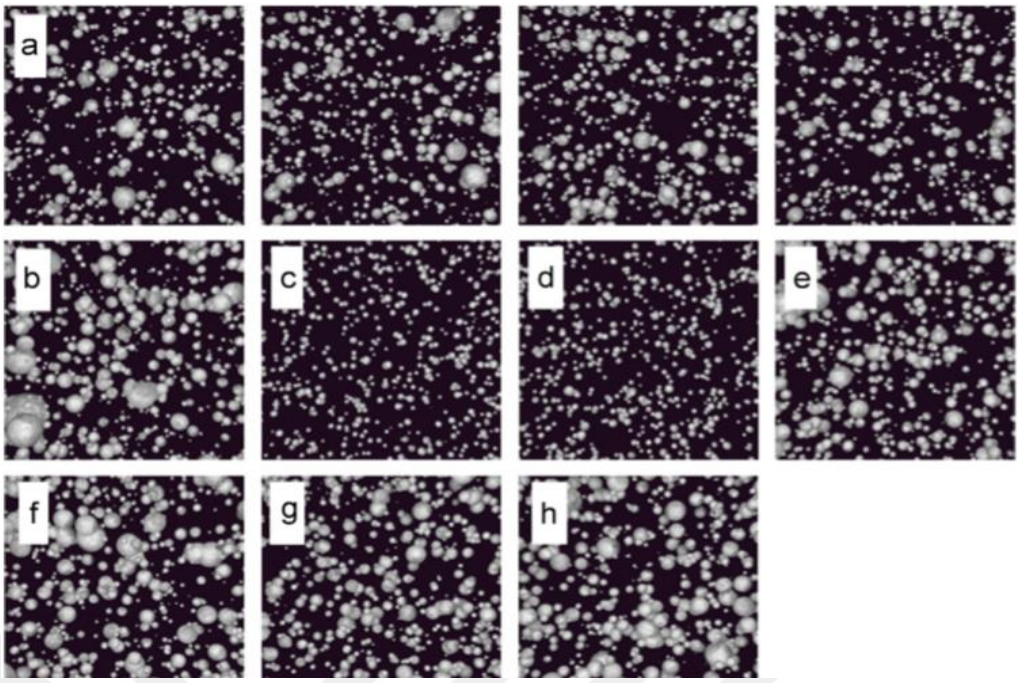

Figure.1.1. Synthetic scanning electron microscope (SEM) images

B. The Methodology

The studies will start to investigation the use of different statistical segmentation algorithms to characterize the EM image nano materials. The limitations of methodologies for SEM nano image processing can be classified based upon three major phases in implementation.

- Using statistical segmentation algorithms, i.e. EM K-means, and Combined EM/K-means.
- Test the segmentation algorithms to characterize the SEM images by Histogram.
- Calculations and mathematical analysis will be conducted by MATLAB.

The method of K-means is according to the following steps. Chosen the (k) data value as the initial cluster centers, then found the distance between every cluster center and every data value and assigned to the nearest cluster. Averages are made for each group, and then this process is repeated until the standard does not match. The following figure shows the flowchart describes the process of k-means algorithm.

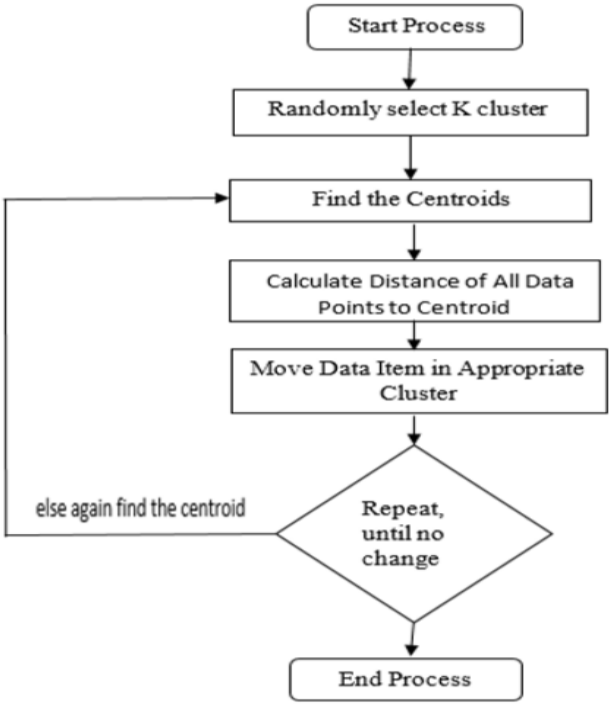

Figure.1.2. K-means Algorithm Process

The EM algorithm classifies each particular pixel through calculating the distance to the center of the class instead of calculating the probability. The figure below shows the flowchart of pixel classification by EM.

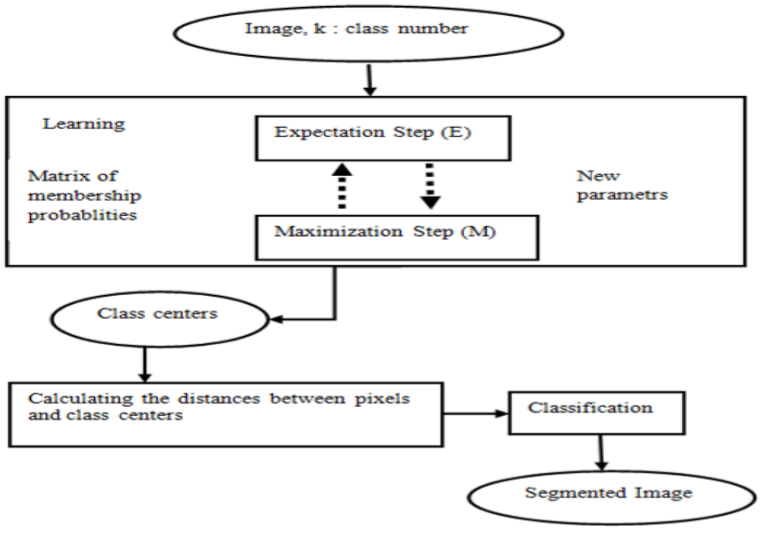

Figure.1.3. Pixels classification by EM algorithms

1.6. Calculations and Metrics

The calculations will be taken for image segmentation by measuring the mean, variance and proportions by the following equations.

$$\text{Mean} = \frac{sum(a^2 * h(a))}{sum(h(a))} \quad \textbf{(1.3)}$$

$$\text{Variance} = \frac{sum\left(a^2\, h(a)\right) - (sum(h(a)) * mean^2)}{sum(h(a)) - 1} \quad \textbf{(1.4)}$$

$$\text{Proportion} = \frac{sum(h(a))}{n} \quad \textbf{(1.5)}$$

Where (a) is the pixel value, h (a) is pixels number in an image with grayscale value a, n is the total pixels number in an image.

For the purpose of algorithms evaluation and comparison, the MSE, PSNR, they are used to measurement the performance of these technologies using segmentation parameters.

- The Mean square error (MSE) it is defined as the mean of the squares of the difference between the expected and actual observations.
- The Peak signal to noise ratio (PSNR) it is defined as the ratio between the maximum possible signal strength and the strength of the corrupted noise that affects the accuracy of its representation. PSNR is commonly used as a metric for image quality reconstruction.

2. BACKGROUND AND LITERATURE REVIEW

2.1. Introduction

Due to advancement of computer learning image-processing techniques are important and widely used for image analysis. The processed images are analyzed to obtain any information or quantitative data from the processed images. Processed image analysis is performed based on pixel properties (such as color or image intensity) by segmenting the image into different segments to obtain information or quantitative data from the processed images (Mui Fu et al., 1981). Image segmentation is the solution for most important problems of image processing today in different segments; segmentation is a part of image processing which has a different type of algorithms to and techniques use. The process consists in dividing the image into regions with many properties such as color, grayscale, texture, brightness, and contrast (Pham et al., 1999).

Several types of segmentation methods have been developed (Mui Fu et al.. 1981). Image segmentation is represented in four categories, namely is thresholding, edge detection, clustering and region extraction, through an automatic or semi-automated process that begins with region extraction (Afifi Afandi_et al., 2019). However, the efficiency of the evaluation of the segmentation algorithms has become the priority to obtain results throughout the process.

This study is used to compare different image segmentation techniques based on SEM images (Krstinic. D, et al., 2013).The beginning of the operation is done by entering a set of SEM image data, and the result of the operation becomes distortions. The segmentation process helps provide more information than is found in SEM images. Several segmentation techniques such as threshold-based segmentation, region-based segmentation, edge-based segmentation, aggregation-based segmentation, and classification-based segmentation all extract the required data from the segmentation process. Through this study, the segmentation method will be used in zoning the SEM image to extract a number of its characteristics (Krstinic D, et al., 2013).

2.2. Nanomaterials Images Background

Over the past years, nano materials have been widely studied by the researchers for their application in the field of chemistry, biotechnology, biomedicine, and in the area of Nano-medicine, etc. Nano materials have been used actively in the ago end years.

Nano material can be classified into organic and inorganic Nano-materials that can be employed for imaging application (Ruma Rani et al., 2019).

Various imaging techniques are available that which one can use it to study the materials or anything else by using different sources of light, such as X-ray, fluorescence, electrons, magnetic resonance, ultrasound and positrons. One of the most important methods that using for imaging the nano-materials is electronic microscopy.

Bio imaging is one of the biological processes that give less interference and three-dimensional images, as it has recently entered the field of nano-biological particles. These techniques are also used in other fields, such as inorganic nano-materials. Among nano materials, magnetic nano-particles, gold nano-particles, carbon nano-tubes, silica nano-particles, quantum dots, fullerenes, and graphene, etc. have been used for imaging applications. Much research has been done on structural image analysis, then processing of images. Image processing techniques are used to analyze micro- and nano-spaces in carbon materials (Oshida K. et al., 2001).

In this work, the authors used various segmentation techniques such as simple thresholding algorithm, Fisher thresholding algorithm, and area segmentation to extract different phases from the SEM image of a polished ceramic patch (Belhomme. P. et al., 2001).By using image-processing techniques, a method has been developed to measure the diameter of electrically spun nano-fibers. In doing so, they used methods such as pruning, skeletalization, etc., to determine the diameter of the nano-fibers (Ficarra. E. et al., 2005).

2.2.1. Scanning Electron Microscope (SEM)

SEM is a microscopic imaging technique and a type of electron microscope that instead of conventional light beams uses electron beams to create magnified images not achievable by the optical microscopy (Goldstein J.I. et al., 2018). In SEM, electrons interact with atoms in the sample and produce various signals that contain information about the surface topography and composition of the sample. The electron

beam is scanned in a point scanning pattern, and then the position of the beam is combined with the intensity of the detected signal to produce the image. The secondary electrons emitted by the atoms excited by the electron beam are rediscovered using a secondary electron detector. The number of secondary electrons depends on the intensity of the signal so that it shows the topography of the sample and obtains accuracy greater than one nanometer.

The principle of operation of SEM is that the image is visualized from data (number, energy, intensity, etc.) of electrons collected by the detector, which are a result of scattering or emission from the sample after being subjected to a focused electron beam produced from an electron gun (Goldstein J.I. et al., 2018; Kazmiruk, 2012).SEM can give information on chemical and physical properties of the material being observed such as size, topography, morphology, compositional structure, crystallography and magnetic microstructures.

SEM proved to be an important characterization technique; it has been widely used by many researchers and research groups to study different features such as morphology and structures of samples (Goldstein J.I. et al., 2018), also the SEM is used to study phenomena that occur during production of composite materials like agglomeration and distribution of fillers in the composite (Mohamed et al., 2017), or phenomena that occur during application of composite materials like the inspection of wear generated surfaces (Goldstein J.I. et al., 2018) or the study of fracture (Ferreira et al., 2017; Vidakis et al., 2016).

2.3. Nano Image Segmentation Strategies

A. Related work in thresholding methods

Threshold is one of the developed segmentation methods, which is the fastest image segmentation technique. Threshold used to segment images composed of bright objects on dark backgrounds and vice versa (Ng, H.F, 2006; Mitsuru. et al., 2012). It is a simple and innate, yet effective technique for image segmentation enables pixels meet the specified criteria considered belonging to the target, are downgraded to the background state.

The important step in image processing is to find an appropriate threshold value to segment an arbitrary object. Threshold in histogram dividing an image into several

regions i.e. object and background. The first part represents the foreground and the second part represents the background. The foreground has pixels with intensity greater than or equal to the opposite threshold, and the background contains pixels less than it (Ng. H.F, 2006; Mitsuru. et al., 2012). Image threshold has many techniques based on parametric or non-parametric approaches. The iterative selection method is one of the first threshold techniques available in the literature (Ridler. T.W.et al., 1978; Trussell H.J, 1979). In this technique, the threshold value initialized firstly by the average of the entire image histogram. The image is segmented to produce two groups G1 and G2 using this initial threshold. After which the average pixel values of G1 and G2 are obtained (Ng, H.F, 2006). Using the first average as the starting threshold, the whole process is repeated until a new threshold is calculated as the average, repeated until convergence is reached.

Various researchers have studied threshold selection methods in recent years (Bansal, 2013). The Otsu method is another popular method that automatically limits the image based on the shape of the histogram (Sahooet al., 1988). The Otsu method has been considered a suitable method for determining the threshold of general images of the real world. The Otsu method is efficient, simple and suitable for automatic threshold selection; it is an optimal global threshold technique (Otsu, 1979; Liao et al., 2001). Align with maximizing the variance between classes of two histogram data sets, which is equivalent to minimizing the variance within the class.

The image to be clipped contains two classes of pixels, namely (the foreground and background) according to the assumption of Otsu technique, then to calculate the optimal threshold by separating these two classes so that their variance is obtained within the category or the minimum variance between the two classes usually by subtracting the variance within the class from the total variance of the complex distribution (Singh et al., 2011; Niblack, 1986).

To improve the images efficiency that has a multi-distribution (multi-modal) method, a search was conducted to introduce new algorithms based on the Otsu method (Trussell. H.J, 1979; Liao et al., 2001; Zaitouna, 2015). (Niblack, 1986) presented in the above-global local threshold method in a way suitable for poorly light and non-uniformly light images. (Niblack, 1986) proposed a new local threshold technique based on the local mean and local standard deviation (Niblack, 1986), compared the

Otsu method and the iterative method, and proposed a suitable and accurate Otsu method to determine the optimal threshold.

B. Related work in K-means and EM

Both examined algorithms have been around for more than 30 years. In 1967, the K-Means algorithm was introduced by name (Mac, 1967).And about ten years later, formalized the EM algorithm was in 1977 (Arthur Dempster et al., 1977). The EM algorithm can be considered as a general algorithm for the K-MEANS algorithm, so these dates mentioned above can be a bit confusing. It is safe to assume that the both algorithms existed before, without a full formulation or explanation of the theory involved. To know and understand how these algorithms work and implement, see that in (Wikipedia).They relied heavily on it. Additionally, some documents in the help section provided limited help. Both algorithms, K-Means and the EM algorithm can be applied to find normal groups in specific data based on different input parameters. Groups of images can be customized based on pixel density, position, color, texture, or a combination of these.

Since both algorithms are subject to termination when a local maximum is reached, not a global maximum (Chris Vutsinas, 2000), the starting locations of the partitions used are very important and can play a role between optimal and non-optimal solutions for both algorithms.

K-Means can be considered as an algorithm based on a complex distribution of information across a given set of departments (Bansal et al., 2013). In each algorithm path, each data value is mapped to the nearest value.

The division depends on some factors of similarity, such as the intensity of the Euclidean distance. The partitions are then recalculated based on these complex assignments. In each subsequent path, the data value can switch partitions, thus changing the partition values in each path. Unlike other clustering algorithms, K-Means usually converge very quickly to a solution. On the other hand, maximizing expectations depends on the easy distribution of data across a defined set of departments. Each data value is associated with each section through a weight-based system (Sahoo et al., 1988). How strongly does the value of data relate to a particular department? EM algorithms rely heavily on the assumption that the values of the initial partitions are close to the natural data sets of the given data (Chris Vutsinas, 2000).

2.4. Nano Image Segmentation Future Trends

Each segmentation algorithm has its own advantages and disadvantages. Nonetheless, there are still a lot of fields for future development by proposing segmentation strategies with extremely high accuracy, sensitivity, and less time complexity. Modified variants of current segmentation can often outperform older segmentation methods. Some modified segmentation algorithms:

- FCM with advanced optimization techniques.
- Marker-controlled watershed segmentation.
- Otsu threshold.

3. NANO MATERIALS ANALYSIS AND CHARACTERIZATION

3.1. Introduction

In materials science, segmentation algorithms have been used to describe the relationship between the microstructure of nanomaterials and their physical properties (Arthur Dempster et al., 1977). However, in order to analyze the microstructure and determine a quantitative description of its morphology or texture, image acquisition techniques such as X-ray micro-tomography or electron backscatter diffraction (EBSD) are often required. Analysis therefore requires image processing, which often requires some kind of semantic segmentation of the image data to detect and extract individual particles, particles, or fibers. The quality of the segmentation has an important influence on the microstructure and macroscopic physical properties of the subsequently analyzed materials (Chris Vutsinas, 2000).

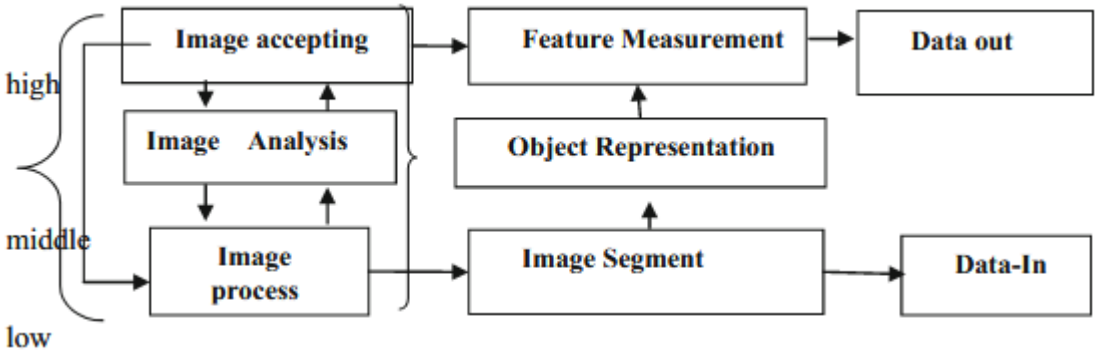

Figure.3.1. Image engineering process

The accuracy of identification assessments was compared between some SEM image segmentation techniques. The best performance analysis is suitable for any computer-aided (MATLAB) analysis purpose. Therefore, in this thesis, we focus on methods that help in image data segmentation.

3.2. Segmentation Methods

Scientists and researchers have recognized various image segmentation methods. Therefore, many of these techniques are very popular, important and frequently used for image segmentation. These are classified as follows (Chuklanov et al., 2006)

- Thresholding based segmentation
- Region based segmentation
- Edge based segmentation
- Clustering based segmentation
- Bayesian based segmentation
- Classification based segmentation

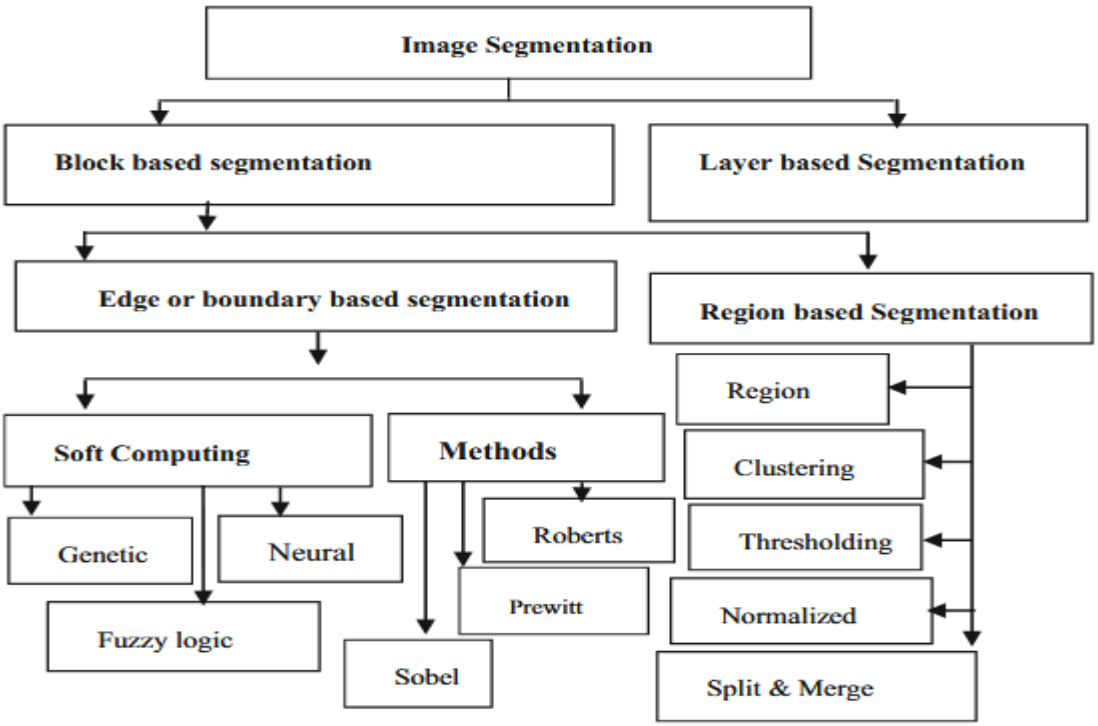

Figure.3.2. Segmentation technique

3.2.1 Thresholding

Threshold is the simplest image segmentation method and one of the most common parallel segmentation techniques. Commonly used segmentation algorithms divide the processing of the grayscale information of the image directly according to the grayscale values of the different targets. This is the method of the maximum variance between classes (Otsu) (Zhang et al., 2008), which selects the optimal threshold at the global level by maximizing the variance between classes.

These methods divide the pixels in the image by their intensity level. These methods are used on images whose objects are brighter than the background. The selection of these methods can be manual or automatic, that is, it can be based on knowledge or preliminary information about the characteristics of the image.

The advantage of the threshold method is that the operation speed is faster, and the calculation is simple. In particular, when the contrast between the target and the background is high, the segmentation effect can be obtained. The disadvantage of this method is that it is difficult to obtain accurate results for image segmentation problems with no obvious grayscale difference or large overlap of grayscale values. Since the spatial information of the image is ignored, only the grayscale information of the image

is considered; it is susceptible to noise and grayscale irregularities and it is usually used in combination with other methods (Wani et al., 1994). There are three types of thresholds: (Zaitouna, 2015; Senthilkumaran, 2006).

A. Global Thresholding: This is done by using any appropriate threshold value$T$. This value of Twill be constant for whole image. Based on T the output image can be obtained from original image as:

$$g(x,y) = 0\ iff(x,y) < Tandg(x,y) = 1\ iff(x,y) \geq T$$

B. Variable Thresholding: In this type of Thresholding, the value of T can vary over the image. This can further be of two types:

(1) Local Threshold: In this the value of T depends upon the neighborhood of $x$and$y$.

(2) Adaptive Threshold: The value of T is a function of $x$and$y$.

C. Multiple Thresholding: In this type of Thresholding, there are multiple threshold values like $T1$and$T2$. By using these output image can be computed as:

$$g(x,y) = 0\ iff(x,y) < T1ORf(x,y) > T2andg(x,y) = 1\ ifT1 \leq f(x,y) \leq T2$$

3.2.2. Edge-based segmentation

The edge of the object is represented by the discontinuous local features of the image, that is, the most significant part of the local brightness changes of the image, such as gray value mutations, color mutations, texture changes, etc (Davis, 1975). It uses discontinuities to detect edges, in order to achieve the goal of image segmentation.

There are always gray edges between two adjacent areas with different gray values in the image and there are discontinuous gray values. This discontinuity can usually be detected using derivative operations, and the derivative operator (Senthilkumaran, 2006) can be used to calculate the derivative. Parallel edge detection is typically used as an image preprocessing method. Widely used first-order differential operators include Prewitt's operator, Roberts' operator, and Sobel's operator (Kundu, 1986). Second-order differential operators include Laplace's operator, Kirsch's operator, and Wallis' operator, as well as other nonlinear operators.

3.2.3. Seeded Segmentation

The Seeded Region Growth (SRG) algorithm is one of the simplest region-based segmentation methods. It performs image segmentation by checking the adjacent pixels of a group of points (called (seed points)) and determines whether the pixels can

be classified into groups of start points (Adams et al., 1994). There is no doubt that the color similarity of each segmented area of SRG is very high and there is no problem of fragmentation. However, it still has two flaws, the initial seed point and the time-consuming problem.

The starting point problem means that different sets of seed points will lead to different segmentation results. This problem reduces the stability of the results of the segmentation of the same image. In addition, since various images have their own appropriate number of divisions, it is important to determine how many starting points should be determined initially. Another problem, and the more serious SRG problem, is time-consuming because SRG takes a long time to calculate. The sub-images are sorted by cluster size, from largest to smallest. The display order is left to right and top to bottom.

3.2.4. Semi-Supervised Segmentation

Semi-supervised semantic segmentation methods existing mainly focus on the design of pseudo-labeling and consistency regularization (Geoffrey et al., 2020). Cut mix augmentation applies on the unlabeled data (Yassine et al., 2020). Show introduces a feature-level perturbation and enforces consistency among the predictions of different decoders. Performs network perturbation encourages consistency between the predictions from the two models by using two differently initialized segmentation models (Yuliang et al., 2020), focuses on improving the quality of pseudo labels.

None of the aforementioned methods explore the biased learning issue in semi-supervised semantic segmentation, though achieving satisfactory improvements over the supervised baseline.

3.3. Statistical based thresholding methods

In some cases, when an image with a number of objects is considered like in SEM images, some of the objects are easily separable from the rest and some objects remain together. In that case, when the objects remain together, it is a challenging task to discover their statistical distributions. While each object is considered as an independent identity and each characterizes a statistical distribution model. This scenario is referred as mixture model (Korting et al., 2007).

To estimate the mixture model there are different ways. One way is to assume that each pixel is a member of one of the distribution model. Then the suitable parameters for the model are estimated. Once the parameters are obtained, then using a suitable distribution formula, the pixels are classified. There are many statistical approaches to fit the mixture model to observed data. They are EM, k-means, minimum distance, etc. We propose to compare and study the different methods discussed above.

3.3.1. K-means

K-MEANS is one of the fastest and most easily used clustering algorithms for image segmentation. This algorithm is simple and uses unsupervised learning to converge to solution. K-MEANS is a popular algorithm that solves clustering problems (Sahoo et al., 1988). Which classifies the given dataset into k clusters based on certain specific distance measurements? A data set can be classified to this certain number of clusters by the algorithm procedure. K-means is a small, repetitive part of a solution applied to many problems. Specifically, k-means are used in Feature Selection, in Subsets Selections problems (Mac, 1967), Statistical data analysis, image analysis, pattern recognition, machine learning, data mining, neural networks, classification analysis and bioinformatics and generally in any problem that requires clustering.

The execution of the k-means algorithm requires high computational cost, which leads researchers to use parallel techniques to implement k-means. MATLAB is a software tool that conveniently supports numerical computations and parallel techniques.

In addition, MATLAB supports parallel computing in computer clusters or multi-core processors CPUs. The algorithms defined as follows:

- Read the SEM image of nano-materials and convert the three-dimensional image into a two-dimensional image.
- Suppose the number of clusters is k.
- Suppose randomly k locations of cluster centers.
- Determine which center is closest to each data point given the characteristics and cluster group numbers.

- Find the center of gravity of each cluster and move the center to that location.
- Repeat until convergence.
- Display the resulting images with histograms.

In our case, the clusters will be in the foreground and background. Then enter the value of k. The center of the clusters is given randomly. We choose to provide the central values of the two peaks of the histogram. The input data set consists of the pixels of the image. Thus, each pixel finds the center to which it is closest. For these new clusters, a center is found. Repeated until there is no more change in the cluster, and the final clusters form the segmented image. Once the mean is determined by the algorithm, the variance and proportions are calculated separately by their respective formulas.

$$\text{Mean}=\frac{sum(a*h(a))}{sum(h(a))} \quad \textbf{(3.1)}$$

$$\text{Variance}=\frac{sum(a^2*h(a))-sum(h(a))*mean^2}{sum(h(a))-1} \quad \textbf{(3.2)}$$

$$\text{Proportion}=\frac{\text{sum(h(a))}}{\text{n}} \quad \textbf{(3.3)}$$

Where (a) is the pixel value, h (a) is the pixels number in the image with gray scale value a, n is the gross number of pixels in an image. Some basic observations to be considered for k-means algorithm are:-

- Initial grouping should be done based on some reasonable assumptions, because initial grouping will determine the algorithm significantly.
- Initially must determine Number of clusters k.
- The algorithm is very sensitive to beginning conditions, so the beginning conditions must be appropriate as different initial conditions may give different results, ultimately affecting the algorithm to a large extent.

3.3.2. Expectation-Maximization (EM)

A general scenario like the observed data a and the set of unknown parameters θ are considered. Let us assume some parameters initially as$p(\theta)$. Then a posteriori probability function is given by $p(\theta/a)$.this is proportional to $p(a/\theta)p(\theta)$. If there is

access to some other data b, then it is easy to maximize $p(a, b/\theta)p(\theta)$,where $p(a, b/\theta)$is related to $p(a/\theta)$ through marginalization (Mitsuru et al., 2012).

$$p(a/\theta) = \int p(b, a/\theta)db \quad \textbf{(3.4)}$$

EM is an iterative procedure between the expectation and maximization step, which converges to a local maximum of the marginal a posteriori probability function

$$p(\theta/a) = p(a/\theta)p(\theta) \quad \textbf{(3.5)}$$

Without calculating the marginal likelihood $p(\theta/a)$. Therefore, EM estimates the probability that the data is present in a certain cluster.

3.3.3. Computation of EM

The image pixels show a different behavior at various parts of the image, so there is a mixture distribution of the pixels. In our case, the mixture distribution produces a probabilistic model composed of two classes, namely foreground and background. The data is assumed to be distributed as Gaussian and the general equation for bimodal Gaussian is

$$g(t) = p_1\emptyset_1(t) + p_2\emptyset_2(t) \quad \textbf{(3.6)}$$

Where $p_1 + p_2 = 1$

$p_1$is the probability that the data is chosen from class 1

$p_2$is the probability that the data is chosen from class 2

$\emptyset_1(\mathrm{t})$ and $\emptyset_2(\mathrm{t})$Denotes the probability density of the two Gaussian distribution

The E-step assigns data points to the closest cluster. The M-step calculates the centroid of gravity of each cluster. Below is a breakdown of how we can solve it mathematically (Imad Dabbura, 2018). The objective function is:

$$J = \sum_{i=1}^{m}\sum_{k=1}^{k} w_{ik}\left\|x^i - \mu_k\right\| \quad \textbf{(3.7)}$$

Where w_{ik} = 1 for data point xi if it belongs to cluster k; otherwise, w_{ik} = 0. Also, μk is the centroid of clusterx^i.

It's a minimization problem of two parts. We first minimize J w.r.t.w_{ik} and treat μk fixed. Then we minimize J w.r.t. μk and treat w_{ik} fixed. Technically speaking, we differentiate J w.r.t.wik first and update cluster assignments (E-step). Then we differentiate J w.r.t.μk and re-compute the centroids after the cluster assignments from previous step (M-step) (Imad Dabbura, 2018), Therefore, E-step is:-

$$\frac{\vartheta J}{\vartheta w_{ik}} = \sum_{i=1}^{m} \sum_{k=1}^{k} \left\| x^i - \mu_k \right\| \quad \textbf{(3.8)}$$

$$f(w_{ij}) = \begin{cases} 1 if k = argmin_{j} \|x^i - \mu_j\| \\ 0 others \end{cases} \quad \textbf{(3.9)}$$

In other words, it assigns the data point xi to the nearest cluster judged by its sum of the squared distance from the cluster centroid.

And M-step is:

$$\frac{\vartheta J}{\vartheta \mu_k} = 2 \sum_{i=1}^{m} w_{ik} \left(x^i - \mu k \right) = 0 \quad \textbf{(3.10)}$$

$$\mu k = \frac{\sum_{i=1}^{m} w_{ik} x^i}{\sum_{i=1}^{m} w_{ik}} \quad \textbf{(3.11)}$$

This results in a recalculation of the center of gravity of each cluster to reflect the new tasks. There are a few things to note here: (Imad Dabbura, 2018). Since clustering algorithms including k-means use distance-based measures to determine similarity between data points, it is recommended to normalize the data to have a mean of zero and the standard deviation of the features will all have different units of measure, such as age and income. Given the iterative nature of k-means and the random initialization of the centroids at the beginning of the algorithm, different initialization may result in different clusters, as the k-means algorithm may converge to a local optimum and not converge to a global optimum. Therefore, it is recommended to run the algorithm with different centroid initialization and choose the result of the run that yields the least sum of squared distances. The assignment of the example does not change the same as does not change within the cluster.

3.3.4. Combined K-means and EM

By aggregating experimental data using both K-means and EM algorithms, the difficult problem of ensuring the accuracy of the results obtained is solved (Yassine et al., 2020), and applied clustering between EM and K-means to quality assessment and comparison datasets based on the use of logistics classification.

When applying logistic regression analysis, K-means and EM clustering methods were compared in terms of accuracy and speed of classification results. Both clustering methods tested showed better accuracy than the EM clustering method alone, showing high accuracy (over 87%) results and high speed. The highest accuracy

(over 94%) was obtained when applying the K-means algorithm, but it took longer than EM. To reduce the time, further optimization is required (Yuliang Zou, et al., 2020).

3.3.5. EM with Initial Values from K-means

Because the main disadvantage of EM is the initial parameters, because EM is more sensitive to the initial parameters. Therefore, the initial parameter should always be assigned a reasonable value. In order to solve this problem in EM and improve its stability and capability, we use the result of k-means as a seed point and perform EM. This is expected to show us some good results. As we expected, this improved EM method showed us some good results of accuracy.

3.3.6. Minimum Distance Estimation

The minimum distance estimators (Trussell, 1979) have shown excellent robustness properties compared to the maximum likelihood, which has practical deficiencies absence of resistance to outliers and general non-robustness with respect to the model specification. Some methods like (Hellinger distance) and (L_1 error) have shown great advantages since they are dimensionless. For these distance measurements, certain approximations are often encountered. Parametric and nonparametric methods rarely use the same estimation criteria. Parametric methods are based on maximum likelihood, while nonparametric methods rely on L_2 (Integrated Squared Error Criterion). The L_2E parameter is derived from the derivation of nonparametric least squares cross-validation and is used to select the bin width h of the histogram. You should now find the integral ∫^g(x) dx and consider minimizing the ISE estimate of h.

3.3.7. Table.3.1. General Comparison of segmentation algorithms

Algorithms	**Complexity & Processing rate**	**Suitable images**	**Segmentation effect**	**Flaw & Suggestions for improvement**
Thresholding	high/very slow	All images	Excellent	The points near boundary may get

				lost, sensitive to the size of mask
Histogram analysis	low/normal	Image with Little noise	Normal	Not stable; sensitive to noise
k-means	Normal, slow	All images	Good, Complexity	sensitive to noise , Some unwanted homogeneity
EM	low/ fast	All image	normal/ stable	The system can only be run for one pass, because more than that, the output will be useless because it causes the partitions to be too similar.

3.4. Summary

Up to now, there are many image segmentation algorithms exist and be extensively used in science and daily life. In this research, we give an examined of several popular image segmentation algorithms that are available, and describe their analysis and implementation using MATLAB.A subjective evaluation can be used to select an optimal result for any algorithm. We will consider the techniques under the following groups: Clustering-based (K-MEANS), EM-based, Threshold-based and histogram-based. To order assessing the effectiveness of these approaches, we will use both the simulated and the real images in our experiments by using some real nano materials images. The simulated data is obtained with different statistical characteristics, and it is tested for all our approaches, once the parameters are obtained by all these methods.

4. ANALYSIS RESULTS AND DISCUSSION

4.1. Introduction

In order to visualize and characterize the nanostructure particle materials, those are obtained from high resolution Scanning Electron Microscope (SEM). The study

uses the segmentation techniques to analyze the captured images and processed it to extract quantitative and qualitative information about many physical properties, including length, size, and density, morphology, and color distribution. The segmentation process is used to make pre-processing to the images to be easier defined by the nanotechnology to get the correct information.

The steps of pre-processing are aimed at contrast enhancement, restoration, compression, background subtraction. The targeted images are in diameters less than micrometers and closed to nanometer. Therefore, the mechanical properties, the surface volume, and the pore size can be emerged by the segmentation. These properties lead to nano-particle structures and give a suitable option for many important high-throughput applications. The properties of physical and mechanical nanoparticles depend not only on the properties of the materials they are made of, but also on their structural properties. Tiny particle sizes and different orientations make the measurement of nanoparticle pores and diameters difficult. For some years now, the image analysis method has made it possible to measure these properties, such as segmentation algorithms.

Threshold approach enables to convert a grayscale image to a binary image by optimal thresholding value. It enables to partition image into pixels as an objects and background. If the pixel value is above a certain threshold, the pixel is associated with the object pixel; however, the lower threshold value is tied to the background pixel. In this chapter, the segmentation's analysis for the realistic powder micrograph images drawn from eight closely related particle size distributions would be evaluated. The images are taken from a database consists of 80 images per class represents scanning electron micrographs of gas atomized powders.

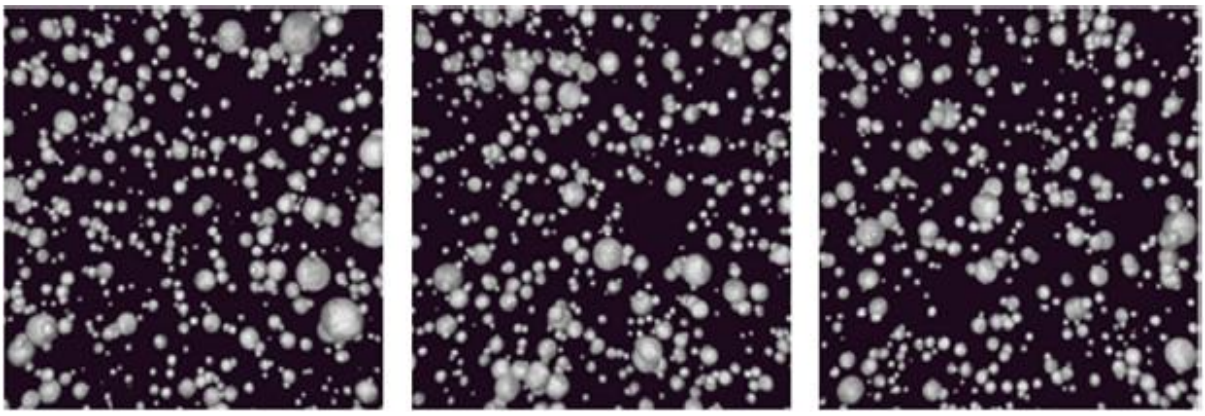

Figure.4.1. Original Image for scanning electron micrographs of gas atomized powders

The microstructure synthesis task for the chosen was performed using Blender. The gas-atomized powders showed in Figure. 4.1 are not spherical and appear to have non-trivial surface roughness. In addition, many particles darken and occlude each other, and smaller particles tend to clump together. The objective of the study is to evaluate the rendered images by using K-Means and EM to identify objects and borders in images. Obtain the computed properties or characteristics, such as colour, density, or texture.

4.2. Materials and Dataset Information

The statistical values of the characteristics were calculated from a sample of the images shown in Figure 1, which shows the particles, by using segmentation algorithms. The analysis helps to understand how the nature and final properties of the powder affect it. These datasets from which the images are studied are data consisting of, 2048 images taken by a scanning electron microscope (SEM) of powder materials and the descriptions of the corresponding 3D structures that they represent. These images were generated using open source rendering software and the generated scripts were included in the dataset.

These data are freely available to use in research in an archive of Mendeley Data "A large dataset of synthetic SEM images of powdered materials sand blast their true 3D structures on the ground (B.L.DeCost; E.A.Holm, 2016). The set of synthetic scanning electron microscope (SEM) powder material images and descriptions of the corresponding 3D structures as a data set of 3D structures and their corresponding 2D images were created using Blender. We considered images as shown in Figure 2,

which are an example of a construction set of 256 independent structure/image pairs for each PSD, resulting in 2048 micrographs of synthetic powder.

4.3. Analysis Method and parameters

In the specific image analysis process, thresholding, EM, and K algorithms are used to determine image details with measurements showing several metrics, including colour distribution, size, and image in a digital gray scale. Algorithms are used to analyse the images by Mat lab (version 2020) to split images and extract features. The image pre-processing steps are shown in Table 1 are the flow of segmentation algorithm in general for the size distribution analysis program.

Table.4.1. Processing the Image Step and Functions

Steps	**Processes**	**Functions Description**
1	Adjusting background illumination	Gaussian filtering
2	Adjusting the contrast	Redistribute Intensity (filtered image)
3	Segmentation	Gray scale and Thresholding
4	Removing dots/noise	Morphological Operation
5	Removing edge objects	Clear Border

4.3.1. Algorithms Description

The algorithms A, B and C are representing the description of the threshold, EM and K-means processes used in image analysis. Simpler threshold methods replace each pixel in an image with a black pixel if the image intensity is less than a constant fixed threshold T or a white pixel if the image intensity is greater than the constant.

Algorithm A :Thresholding Processes

1. **Read image:** *SEM image of powder micrograph images*
2. **Set :***Initiate Threshold value*
3. **Calculate:** *the image pixels*
4. **IF:** *the last pixel*
5. **Apply:** *threshold value to image*
6. **Set:** *output image*
7. **Else**

get value: *surrounding pixels*

8. **Compare:** *the calculated value with exiting threshold*

9. **Calculate:** *the mean value*
10. **Set:** *threshold value*
11. **Go To:** *step 4*
12. **End**

The Expectation Maximization (EM) algorithm is an iterative method for finding the maximum (local) probability or maximum subsequent estimate (MAP) of parameters in a statistical model, where the model is based on unobserved latent variables. EM iterations alternate between a wait phases (E), which creates a function to predict the log-likelihood evaluated using the current parameter estimates, and a maximization phase (M) that computes the parameters that maximize the expected value.

Algorithm B: EM Processes

1. **Read Image:** *SEM image of powder micrograph images*
2. **Set :** *initialize the hypothesis (**number of Gaussian, Estimated mean values**)*
3. **Set Expectations:** *Estimate expected values using hypothesis based on standard deviation*
4. **Set Maximization:** *provides new estimate of parameters* ***(mean of image iterations and dimensions)***
5. **Check conditions: check the** *hypothesis with defined threshold value*
6. **If yes**
7. *output image*
8. **Else**
9. **Go To:** *step 2*
10. **End**

The K-means clustering algorithm is an unsupervised algorithm that is widely used to segment the area of interest from the background. However, before using the K-means, a major partial stretch enhancement is applied on the image to improve the quality of the image.

Algorithm C: K-Means Processes	
1.	**Read Image:** *SEM image of powder micrograph images*
2.	**Set cluster numbers:** *clusters umbers*(**2, 4, 6 or more**)
3.	**calculate:** *the value of K-means iteration*
4.	**Set:** *locations of cluster centers randomly*
5.	**Set:** distances and labels in relation to features and cluster group numbers.
6.	**Calculate**: *the centers of each cluster group*
7.	**Calculate:** *cluster points and the new cluster centers*
8.	**Result:** *analyses images*
9.	**Output:** *histograms*

4.3.2. Image Analysis Metrics

The metrics used to analysis the algorithms performance in images segmentation are the image size and histogram. Using Image Histogram equalization to identifies particles and pores in nano-particle images to obtain intensity differences between powder particle pixels and pores. Equalizing as the intensity of powders particles increases against the image background can make the difference in intensity for powders particles and pores. Another metric is the SSIM index, which evaluates the image quality as the best image obtained by an algorithm applying the equation to the reference image. SSIM is measured over several frames of the image. The SSIM is measured over several frames of the image. The measurement between two frames x and y in the N × N dimension are as follows.

$$\text{SSIM}(x, y) = \frac{(2\mu_{x*}\,\mu_{y+}\,C_1)(2\sigma_{xy}+C_2)}{(\mu_{x+}^2\,\mu_y^2+C_1)(\sigma_x^2+\sigma_y^2+C_2)} \quad \textbf{(4.1)}$$

Where, μx and μy represents the means of X and Y respectively. In addition, the σ is for variance. The constant C1 and C2 can be calculated as follows.

$$C1=(K_1L)^2 \quad \textbf{(4.2)}$$

$$C2=(K_2L)^2 \quad \textbf{(4.3)}$$

This is equations are used to calculate between each two frames in the image, for the whole image quality evaluation, the calculation taken by the following equation.

$$\text{MSSIM}(x, y) = \frac{1}{M}\sum_{j=1}^{M} SSIM\ (x_j, y_j) \quad \textbf{(4.4)}$$

Where X is the base (original) image and Y is the output image of every algorithm to be compared.x_j , $y_j$represent the content of the j^{th} local view and M is the number of local views with inside the image.

4.4. Evaluation Results and Discussion

In this study, to determine the threshold of the nano-materials sample and extract its properties, the K-means and EM algorithm are also applied and compared. The analysis is performed on four images selected randomly from the SEM dataset as a sample of powders particles, and the output results are divided into four samples as follows.

A. First Image (Sample 1)

In this sample, the selected image has an average pore radius equal to 6.3529, the porosity is about 0.6874. The standard deviation is calculated by 3.2505. The original image is shown in fig 4.2 with a resolution equal to 0.4590. The results of segmentation by the algorithms are shown in the fig 4.3, 4.4, 4.5 and 4.6.The MSSIM index related to the used methods is shown in fig 4.7, which reviews the comparison of the threshold, EM and K-means quality.

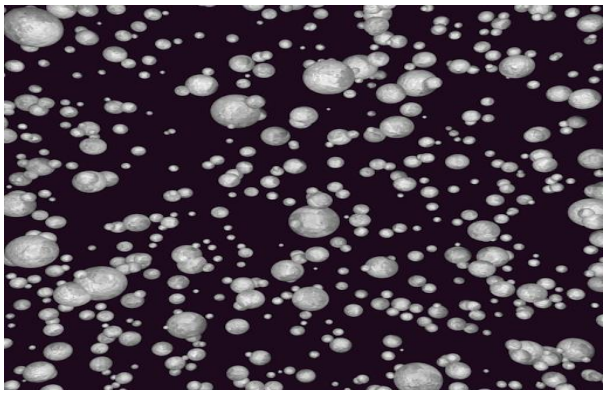

Figure.4.2. Original Image of gas atomized powders (sample 1)

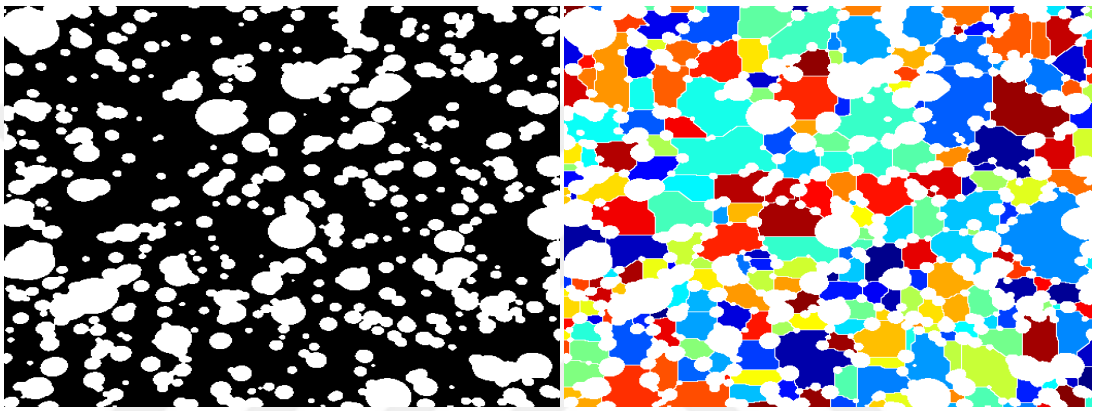

Figure.4.3. (a) After Threshold Process, (b) After Threshold with RGB Label (sample 1)

The simulation is taken to evaluate the segmentation algorithm by taking the first image sample as shown in figure 4.2. After segment the original image by the threshold process, the obtained results is shown in figure 4.3 (a) shows the image after threshold process in gray colour. By considering the colour function, the output of threshold image with RGB Label shown in figure.4.3 (b). The RGB shows the particles bounders in colour levels. The white shapes represent the particles in the image.

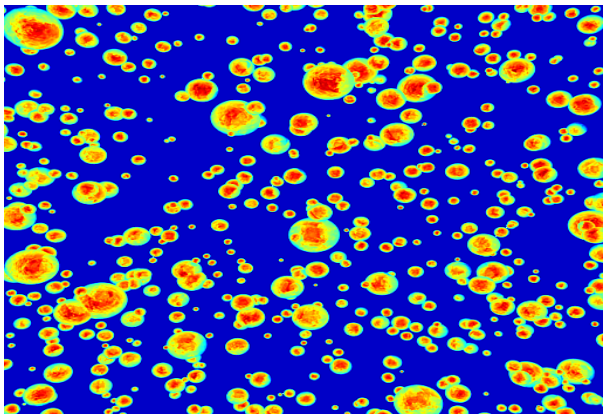

Figure.4.4. After k-means Process (sample 1)

Figure 4.4 represents the output of sample 1 image after using k-means algorithm. Since the k-means is used for clustering purposes as an unsupervised machine learning to cluster the similar objects in-group, it helps to extract the features of particles samples be determining the colour of the object in the nano-image. This process helps to determine the amount of light that hits the object, and thus with each other, the descriptions of the images in terms of these components help to distinguish the object in terms of hue, lightness, and density.

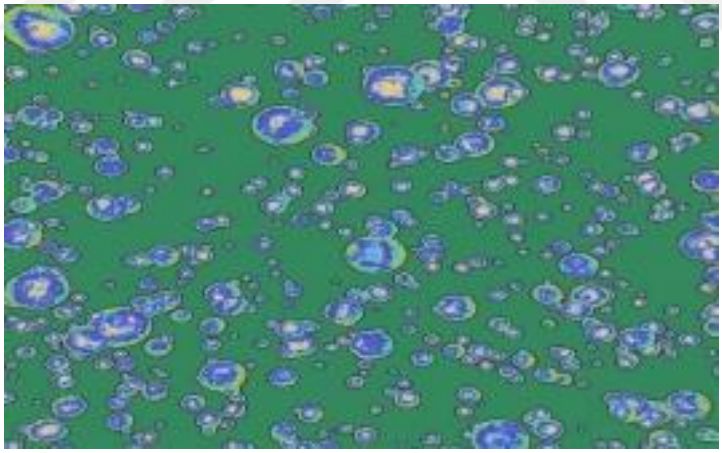

Figure.4.5. After EM Process (sample 1)

Figure.4.5. showed the sample image after considering the process of EM algorithm to the original image. This algorithm estimates the parameters of the Gaussian Mixture Model (GMM), which represents the required number of sections and fits into an image histogram using a combination of Gaussian distributions and provides a sorted image. It expresses a mixture of multivariate natural densities, which

is defined as classifying pixels at a dynamic similarity distance. The EM helps classify of noisy pixels in image.

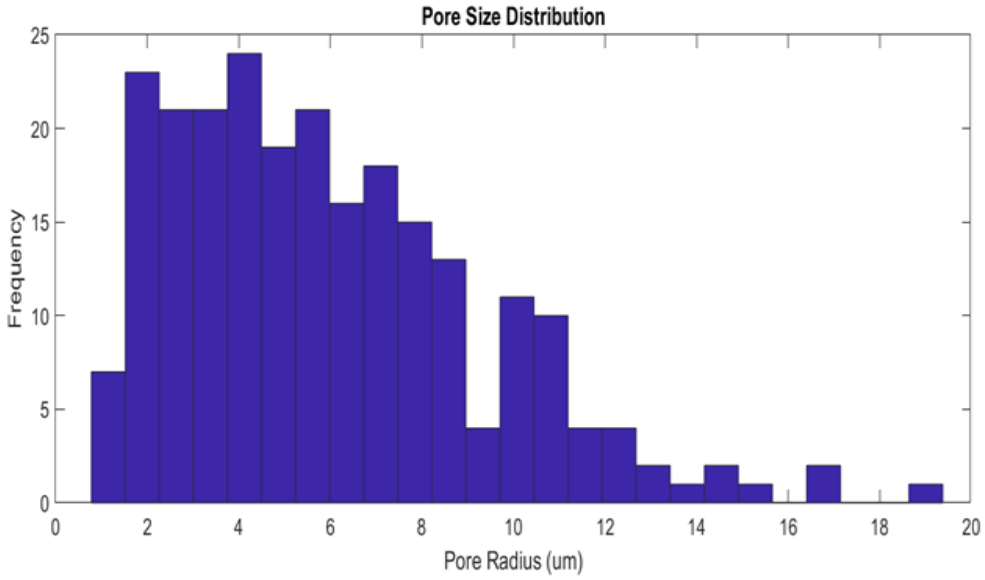

Figure.4.6. The Histogram of Analysed Image (sample 1)

Figure.4.6. showed the histogram of analysed image after considering the thresholding process. Histogram helps to know the brightness of the image by looking at the histogram and observing the spatial distribution of image values. This plot shows the pore size of the particles for the thresholding image.

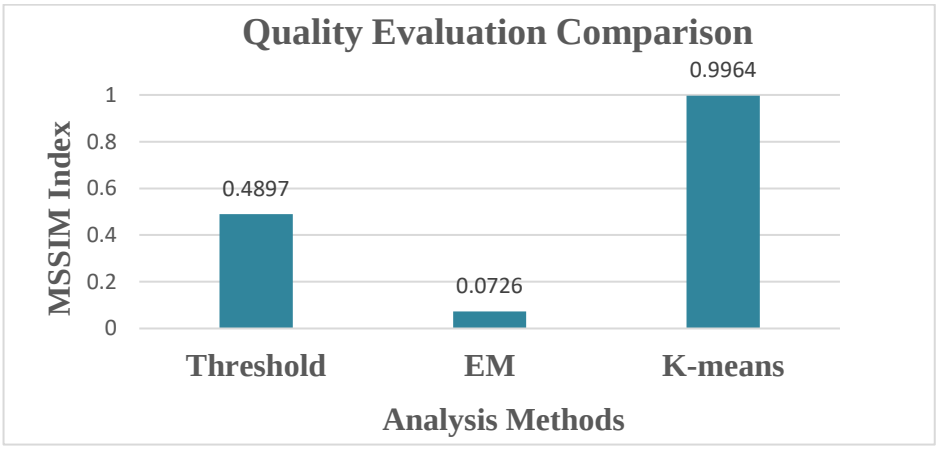

Figure.4.7. Quality Assessment of Analysis Methods Related to (Sample 1)

The comparison between the threshold, k-means and EM algorithms in terms of MSSIM is shown in figure 4.7. The figure shows that k-mean gives higher MSSIM index than the threshold and EM by 49% and 7.3% respectively.

B. Second Image (Sample 2)

In the image sample 2, the selected image has an average pore radius equal to 5.9945, the porosity is about 0.6698. The standard deviation is calculated by 3.4037. The original image is shown in figure 4.8 with a resolution equal to 0.4590. The results of segmentation by the algorithms are shown in the figure 4.9, 4.10, 4.11 and 4.12, the MSSIM performance shown in figure.4.13.

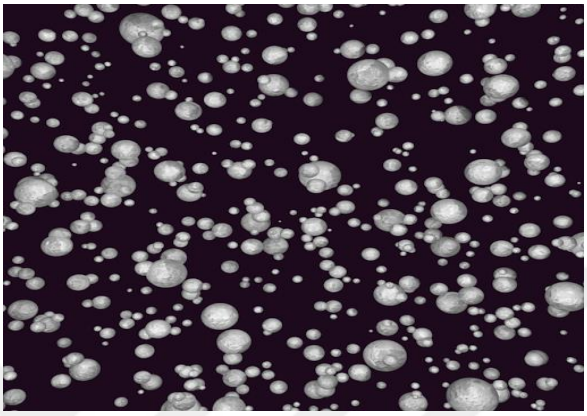

Figure.4.8. Original Image of gas atomized powders (sample 2)

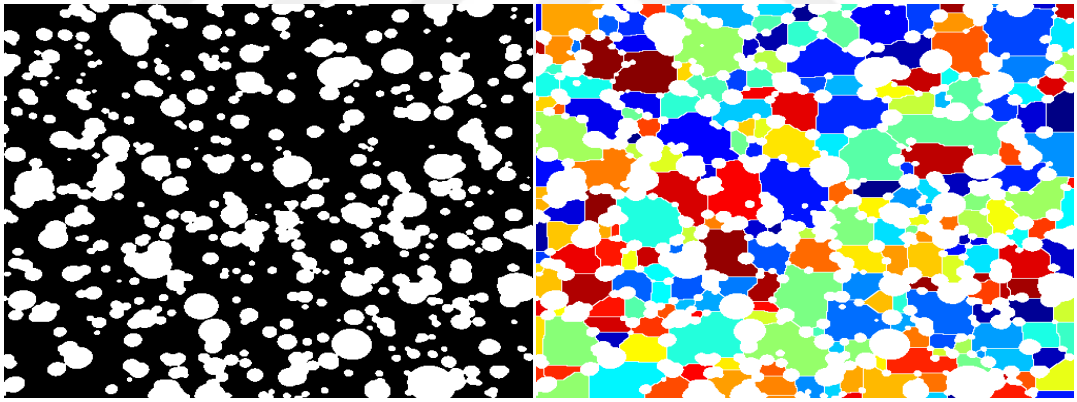

Figure.4.9. (a) After Threshold Process, (b) After Threshold with RGB Label (sample 2)

Figure 4.9 (a) and (b) show the second image sample after threshold process in gray scale and RGB level respectively. In figure 4.9 (b) the output shows the size of the particles in white colour with the pore size between them.

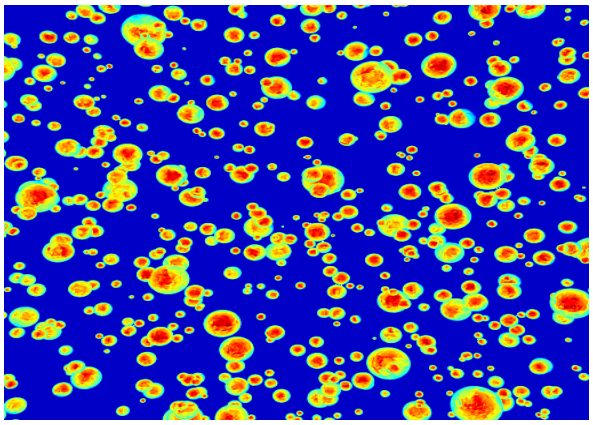

Figure.4.10. After k-means Process (sample 2)

Figure 4.10 shows the output of k-means segmentation for the second image sample. The result images extract the reflects of the light from the particles in ranged colours to show the image density.

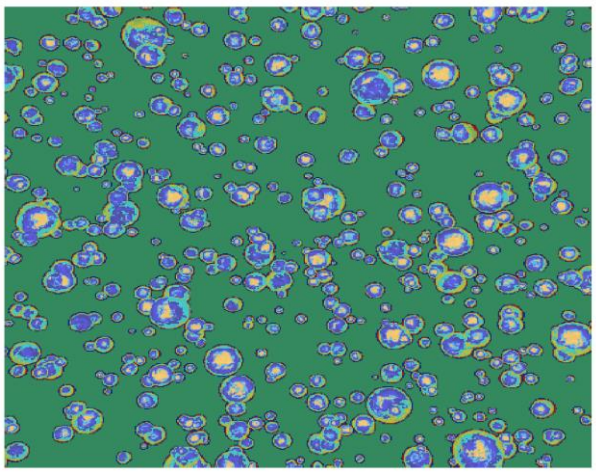

Figure.4.11.After EM Process (sample 2)

The output of EM algorithm after taking the second image sample is shown in figure.4.11.Compared with the k-means, the EM results is quite weak in recognize the density of the particles in image and the pore size distribution in clear.

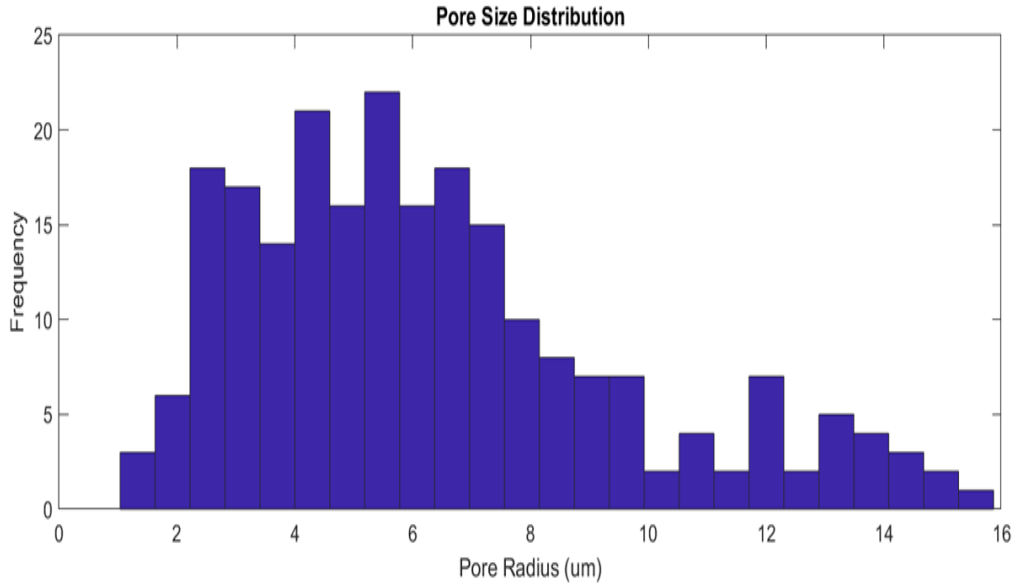

Figure.4.12. The Histogram of Analysed Image (sample 2**)**

In the histogram taken for the second sample image, the results showed that pore size is distributed on along all the radius of particles as shown in figure.4.12.The results of core analysis for the particles size show that most of the pores with higher frequency have a radius between 2 to 8 μm and about 19% of the pores have the highest frequency.

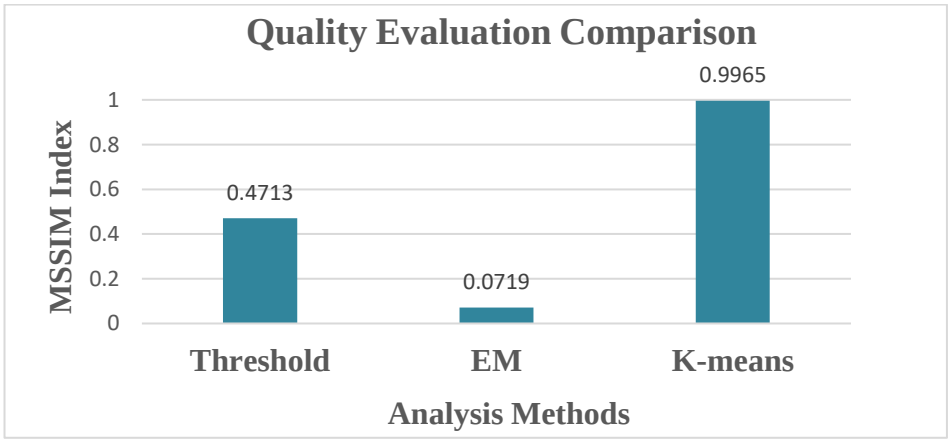

Fig.4.13. Quality assessment of Analysis Methods Related to Sample 2

The comparison between the threshold, k-means and EM algorithms in terms of MSSIM is shown in figure.4.13. The figure shows that k-mean gives higher MSSIM index than the threshold and EM by 47.3% and 7.2% respectively.

C. Third Image (Sample 3)

For the third sample, the selected image has an average pore radius equal to 6.1852, the Porosity is about 0.6772. The standard deviation is calculated by 3.2552. The original image is shown in fig 4.14 with a resolution equal to 0.4590. The results of segmentation by the algorithms are shown in the fig 4.15, 4.16, 4.17 and 4.18.The MSSIM performance shown in fig 4.19.

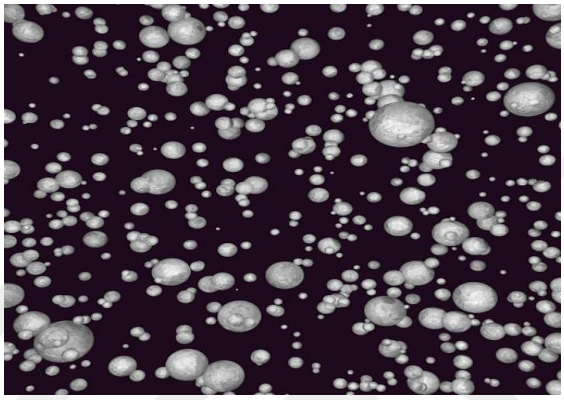

Figure.4.14. Original Image of gas atomized powders (sample 3)

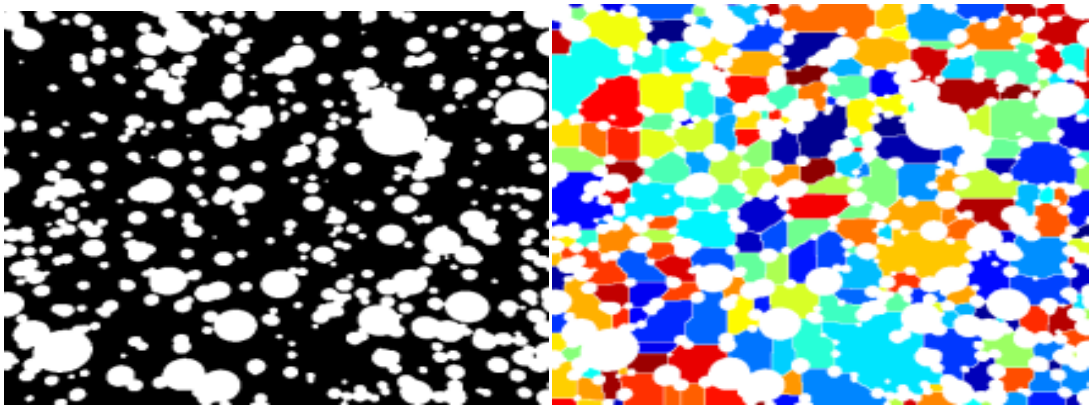

Figure.4.15. (a) After Threshold Process, (b) After Threshold with RGB Label (Sample 3)

In figure.4.15 after using the threshold process, we get image segmentation in gray colour as in (a) and in RGB as shown in (b). Compared with first and second sample images, the particles are large and distributed with less dense.

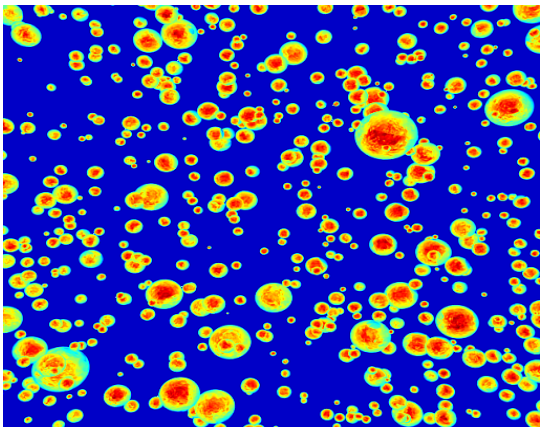

Fig.4.16. After k-means Process (sample 3)

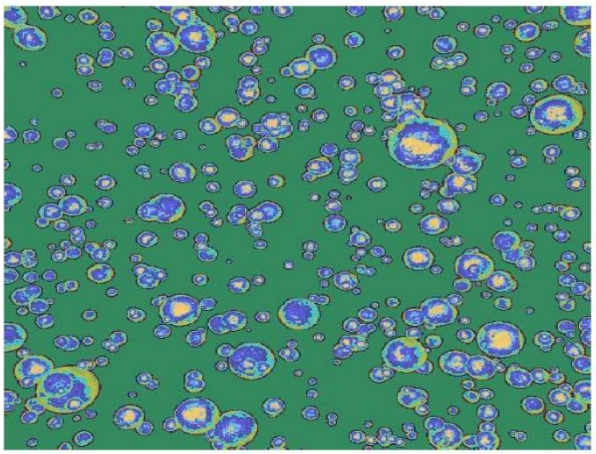

Figure.4.17.After EM Process (sample 3)

In figure.4.16.the third sample image is segmented by k-means algorithm. The results showed that increasing in the dimensions of the particles in the image will affects the deletion of some other elements after k-means and EM as well as shown in figure.4.17. The observation is that when conducting the analysis, a number of elements are removed even though they are not important.

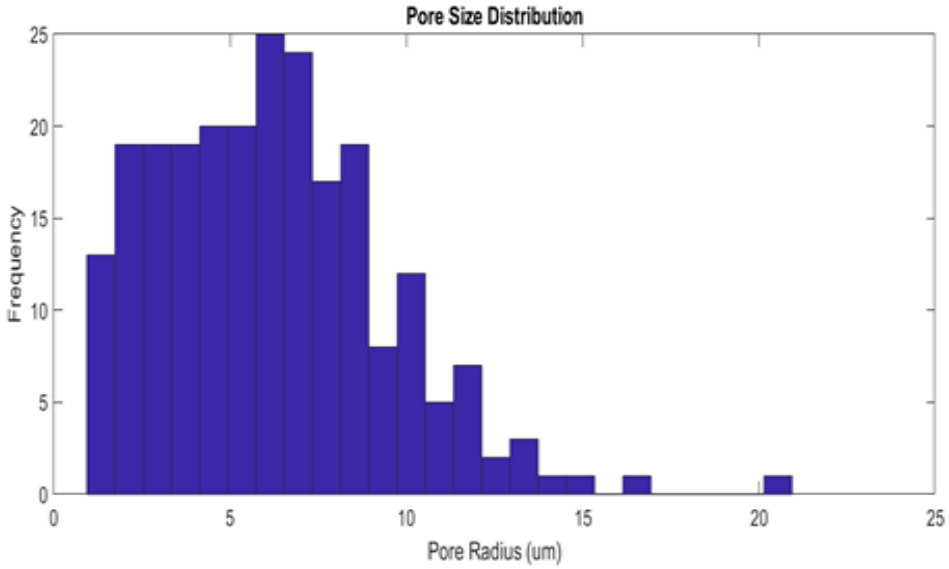

Figure.4.18. The Histogram of Analysed Image (sample 3)

Figure.4.18. showed the histogram of pore size distribution for the third sample image. The main importance of the pore size distribution histogram lies in its use to monitor the size distribution of particles and how they relate to each other. The histogram shows that the values are more closed to the left side, with high pore size distribution frequency for related powder micrograph material.

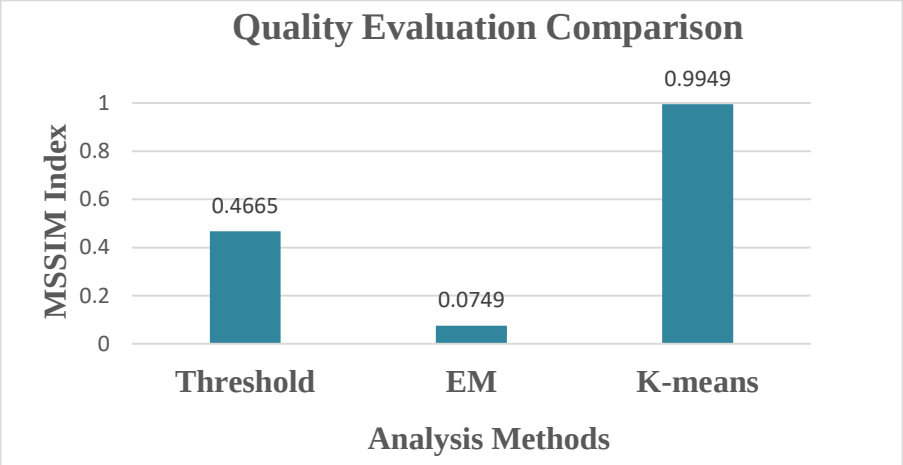

Figure.4.19.Quality assessment of Analysis Methods Related to Sample 3

The comparison between the threshold, k-means and EM algorithms in terms of MSSIM is shown in figure 4.19. The figures show that k-mean gives higher MSSIM index than the threshold and EM by 46.8% and 7.5% respectively.

B. Fourth Image (Sample 4)

The selected image sample 4 has average pore radius equal to 6.1887, the porosity is about 0.6675. The standard deviation is calculated by 3.2441. The original image is shown in figure 4.20 with a resolution equal to 0.4590. The results of segmentation by the algorithms are shown in the figure 4.21, 4.22, 4.23 and 4.24.The MSSIM performance shown in figure 4.25.

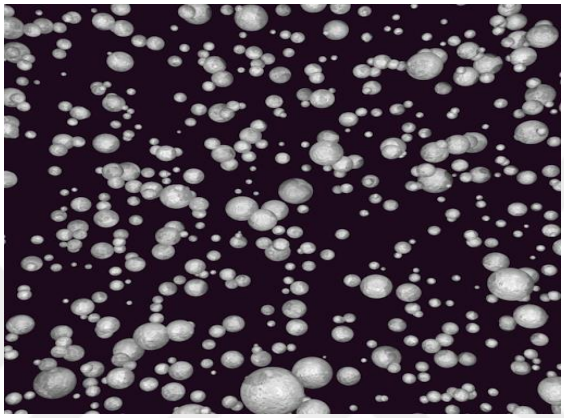

Figure.4.20. Original Image of gas atomized powders (sample 4)

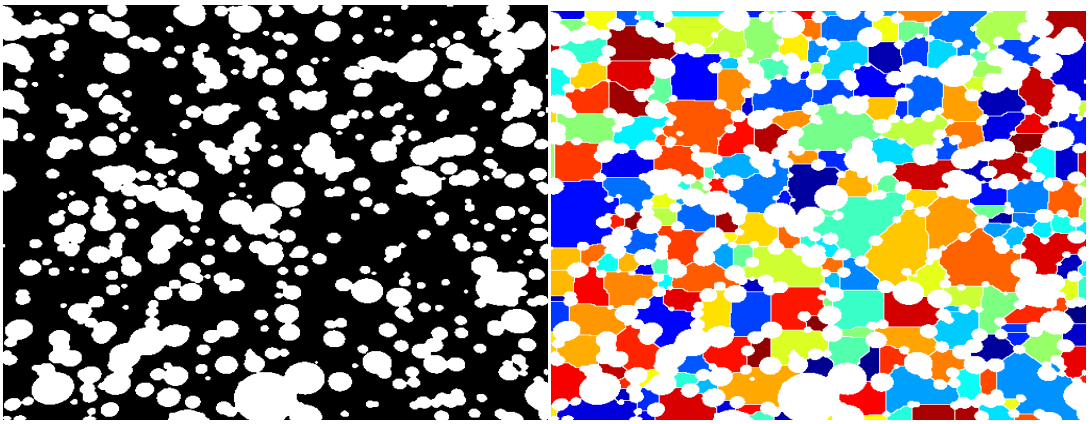

Figure.4.21. (a) After Threshold Process, (b) After Threshold with RGB Label (Sample 4)

The threshold process taken for the fourth sample image is shown in figures 4.21 (a) and 4.21(b), for the gray scale and RGB label respectively. As the same observations extracted from the three previous samples, the threshold process shows the particles bounders in colour levels and the particles in white shapes.

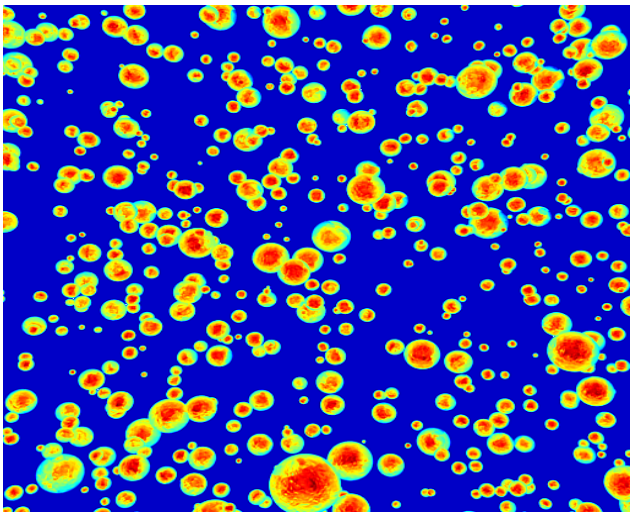

Figure.4.22. After k-means Process (sample 4)

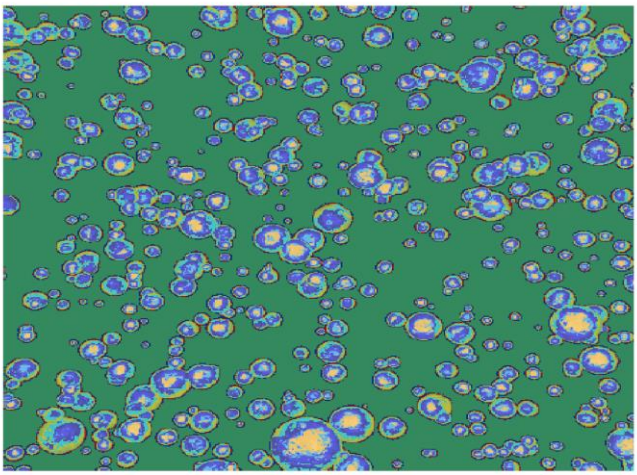

Figure.4.23. After EM Process (sample 4)

The result of sample (4) segmentation by the k-means and EM algorithms is shown in figures 4.22 and 4.23. As the same as in first sample, the algorithms clearly extract the features of particles in image to show its density and distribution.

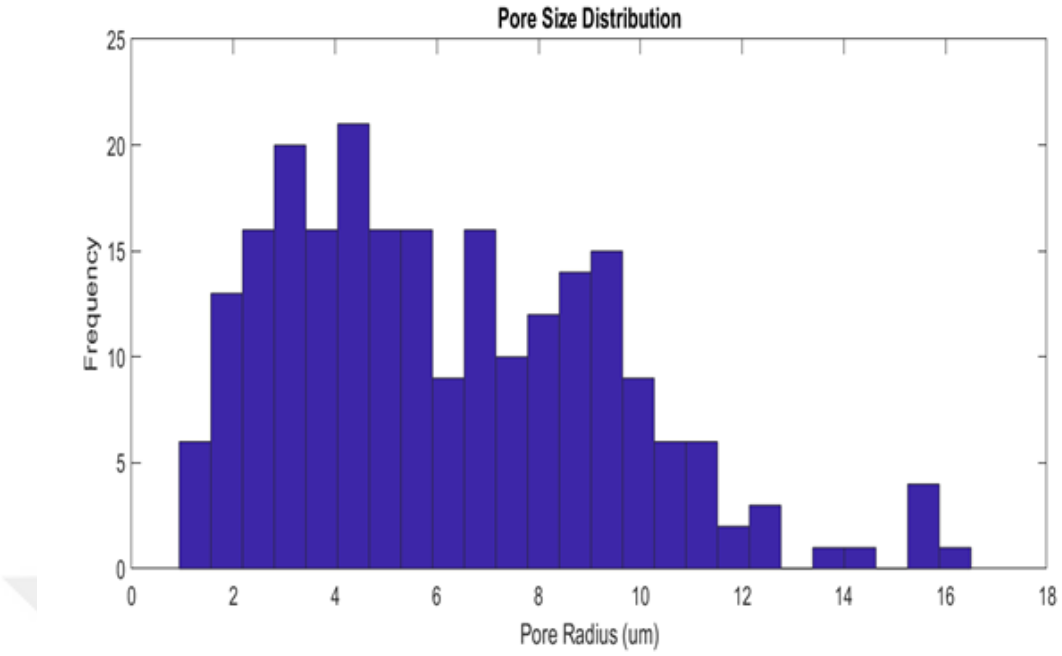

Figure.4.24. The Histogram of Analysed Image (sample 4)

The image histogram is given by figure 4.24 to analyse the image after considering the thresholding process. The result shows the particles brightness and spatial distribution of image values. It also observed the pore size distribution frequency for the particles in the image.

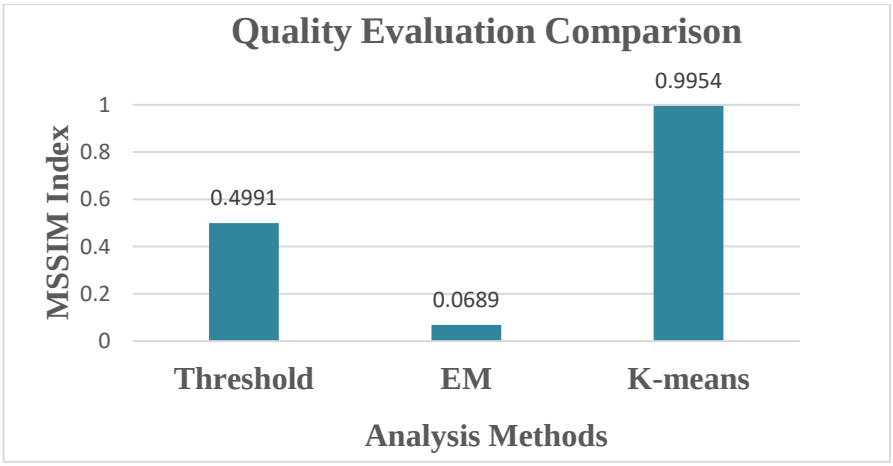

Figure.4.25.Quality assessment of Analysis Methods Related to (Sample 4)

The comparison between the threshold, k-means and EM algorithms in terms of MSSIM is shown in figure 4.25. The figure shows that k-mean gives higher MSSIM index than the threshold and EM by 50% and 6.9% respectively.

For all the image samples analyzed above, after the use of the statistical approaches, we obtain the image segmentation. The analysis adapts to the background of the images and to the background histograms for the Gaussian curves.

The optimization was discovered by solving a set of equations by using different parameters of a mixture of an aggregate of Gaussian distributions to determine the optimal threshold using statistical approaches. Through analysis, the results obtained from the image segmentation process show the strong correlation of parts of the image with objects or areas of the image.

When the images have been processed with the process of separating pixels, for each selected image and determining pores and dimensions. In the threshold images obtained by the aforementioned algorithms, we noticed that in all the analyzed images, the images obtained by the local threshold method give a better result than the global threshold.

From the observations observed in the results of the histograms, as shown in Figures 4.6, 4.12, 4.18 and 4.24, it was found that when the size of the image is increased, the effect of removing certain elements on the images decreased, although the increase. The number of items removed is not an important property of the images. This functionality is beneficial to exploit those elements in a certain way in applications related to nanotechnology. From figures 4.7, 4.13, 4.17 and 4.25 relating to the image quality after the methods used, we have observed that the K-means method offers better performance than the EM and threshold methods.

In general, the SSIM index for image quality assessment obtained from all K-means image samples is much closer to 1, and therefore indicates that the K-means method better segments gas atomized powder images than the others.

In general, it is observed that during the execution of the EM algorithm, the performance degrades rapidly due to the variables initialized in the algorithm, because they are very sensitive to their initial values. Moreover, using K-method is likewise very touchy to small datasets, and overall performance, that may deteriorate at any time.

However, while the information of the photo facts is huge, the overall performance will increase rapidly. The algorithm works thoroughly even if the number

of groups is low; the whole scenario helped the algorithm perform well for this test case.

4.5. Summary

As can be seen by the results and as expected, the K-Means algorithm showed better results. Where the results were good for image segmentation and the implement was simple fairly. As also can be visible from the results, the quantity of partitions used with inside the k-means segmentation has a very large impact at the output. By the using extra partitions, with inside the RGB setup there are as many colours as possible to display in the output, the same goes for the parameter that controls the intensity of the gray scale in the threshold algorithm.

Apparently from the results of the EM algorithm there is a problem when all sections converge to the same values. So, to get something that looks like the good output, it has simply done eliminates the effect of some pixels with a weight on the change in partitions. Through histograms observation, the segmentation approach showed better results and has retained its robustness considerably at all image samples. Therefore, the results shows that, K-means as expected shows a better performance compared to EM by retaining the structure of the particles with little loss of data, removes a lot of noise, but still has minute holes.

5. CONCLUSION AND RECOMMENSATION

The SEM nanomaterials images have been segmented using different statistical methods like EM, k-means and histogram method. The segmentation processes works fine for SEM images with less noise. The statistical techniques that we have studied for thresholding seem to work better than standard automatic thresholding methods like Ridler, Otsu and Calvard method.

The segmentation techniques can also be applied to the AFM nanostructure image to extract information such as length, diameter of the nanostructure to find the total surface area. Also, finding the degree of blurriness would help in determining the relative distance between the nano-structure in different zones.

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