IMAGE SYNTHESIS TECHNIQUES FOR FEATURE EXTRACTION

A Thesis submitted in partial fulfillment of the requirements for the award of the Degree of

MASTER OF ENGINEERING
IN
ELECTRONICS AND COMMUNICATION ENGINEERING

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CERTIFICATE

I, **Aditya Sharma**, hereby certify that the work which is being presented in the thesis entitled, "***Image Synthesis Techniques for Feature Extraction***", in partial fulfillment of the requirements for the award of degree of Master of Engineering in Electronics and Communication Engineering submitted in Electronics and Communication Engineering Department of Thapar University, Patiala, is an authentic record of my own work carried out under the supervision of **Dr. Amit Kumar Kohli** and refers other research works which are duly listed in the reference section.

Aditya Sharma

Dated:- 24 / 06 / 2011

This is to certify that the above statement made by the candidate is correct and true to the best of my knowledge.

Dr. Amit Kumar Kohli
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Dated:- 24 / 06 / 2011

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ABSTRACT

The main objective of this dissertation is producing statistical analysis for quality check of membrane filter using Image Processing. Quality of membrane filter is determined by uniformity factor of the polymer beads under test.

Membrane filters or "membranes" are micro-porous films with specific pore size ratings. Membranes retain particles and microorganisms that exceed their pore ratings by acting as a physical barrier and capturing such particles on the surface of the membrane. This dissertation aims at producing a system which generates statistical data for quality check of membrane filter using image processing. Uniformity factor of the polymer beads determines the quality of the given membrane filter.

Through this work results are presented from a study where the membrane filter is analyzed for its operating functionality using various feature extraction techniques such as Watershed, Active Contouring, Global thresholding, Circular Hough transform, etc. The ultimate goal is to use this information for analyzing the operating efficiency of a membrane filter. The images represent the filter with different no. of beads along with their boundary extracted images. We obtain good results for separate beads along with relatively complex overlapping beads.

According to the quality of the membrane filter obtained it can be used for various applications within the industry, science and research. Some of applications are water recovery and recycle, fluid and water purification, capture and recovery of fluid suspended products (biological, minerals etc.), desalination of water, medical and pharmaceutical use, bacteriological examination in air and water and food and dairy industry.

Keywords—*Membrane filter, active contouring, global thresholding, circular hough transform, watershed.*

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LIST OF ACRONYMS

BMF	Beer Membrane Filtration
CHT	Circular Hough Transform
DT	Drowning Threshold
ERR	Equal Error Rate
FAR	False Acceptance Rate
GIW	Gradient Inverse Weighted
HT	Hough Transform
IHPF	Ideal High Pass Filter
ILPF	Ideal Low Pass Filter
LOG	Laplacian of Guassian
MD	Maximum Deviation
MF	Membrane Filter
MPN	Most Probable Number
NTSC	National Television System Committee
RO	Reverse Osmosis
ROI	Region of Interest
SNR	Signal to noise ratio
STD	Standard Deviation
UF	Ultra Filtration

CHAPTER 1

INTRODUCTION

Membrane filters are constructed very thin layers from polymers and other advanced synthetic materials. Membrane filter thickness varies from 100 to 300 micro-meters. Most are designed and manufactured with approximately 70 to 90 percent porosity. The porosity is normally specified by the filter manufacturer and effectively controls the fluid flow rate and particle capture size. Porosity and effective filtration area should be matched for absorption, flow requirements, and medium binding requirements.

Membrane filters are available in standard and custom sizes, shapes and materials. Some common materials used are; MCE (nitrocellulose), Cellulose Acetate, Coated PTFE (Teflon), Hydrophobic PTFE, Nylon, polycarbonate, Glass. So taking the image of the sample, processing it to get the area of beads and then statistically analyzing it to study its uniformity is the task being done in this dissertation. Polymer beads are the tiny polymer particles used to make membrane filters. These particles are spherical in shape. Since they are of very small size so their shape and size cannot be judged with a naked eye. A microscope has to be used under which judging its shape and size is easy. But by just looking at these beads we can only roughly estimate their uniformity. Here the plan is to develop a semi automated system to check the uniformity of polymer beads. Uniformity of beads is needed as it directly affects the quality of membrane filter. Higher is the uniformity in size greater will be the quality of produced filters.

This dissertation work is related to microscope image processing [1] using the image processing operation image segmentation.

Microscope image processing is a broad term that covers the use of digital image processing techniques to process, analyze and present images obtained from a microscope. Such processing is now commonplace in a number of diverse fields such as medicine, biological research, cancer research, drug testing, metallurgy, etc. A number of manufacturers of microscopes now specifically design in features that allow the microscopes to interface to an image processing system.

1.1 Image Segmentation

Image Segmentation is technique used to find objects of interest from the background. The object pixels would be black (0 intensity) and background pixels white (max intensity). Segmentation refers to the process of partitioning a digital image into multiple segments. The goal of segmentation is to simplify and/or change the representation of an image into something that is more meaningful and easier to analyze. The result of image segmentation is a set of segments that collectively cover the entire image, or a set of contours extracted from the image. Each of the pixels in a region are similar with respect to some characteristic or computed property, such as color, intensity, or texture. Adjacent regions are significantly different with respect to the same characteristics Image segmentation.

1.2 Medical Image Segmentation

Medical Image Segmentation [2], [3] is one of the most important parts of clinical diagnostic tools. Medical image segmentation refers to the segmentation of known anatomic structures from medical images. Structures of interest include, tumors and cysts, as well as other structures such as bones, vessels, brain structures . The overall objective of such methods is referred to as computer-aided diagnosis; in other words, they are used for assisting doctors in evaluating medical imagery or in recognizing abnormal findings in a medical image segmentation results of brain.

1.3 Methods of Segmentation

Methods of Segmentation Images are often interfered by signals and artifacts which rose of during sampling, what may cause big problems at using of common techniques of segmentation. Therefore, accurate segmentation of medical images is a very difficult task. However, the process of accurate segmentation of these images is very important and crucial for a correct diagnosis by clinical tools. Many methods have been developed for better image segmentation. Thresholding & Active Contour Method are among them.

1.3.1 Thresholding

Thresholding [4] is the simplest method of image segmentation. From a grayscale image, thresholding can be used to create binary images. Image thresholding is a common task in many computer vision and graphics applications. The goal of thresholding an image is to classify pixels as either "dark" or "light".
During the thresholding process, individual pixels in an image are marked as "object" pixels if their value is greater than some threshold value (assuming an object to be brighter than the background) and as "background" pixels otherwise. This convention is known as threshold above. Variants include threshold below, which is opposite of threshold above; threshold inside, where a pixel is labeled "object" if its value is between two thresholds; and threshold outside, which is the opposite of threshold inside, an object pixel is given a value of "1" while a background pixel is given a value of "0." Finally, a binary image is created by coloring each pixel white or black, depending on a pixel's label. Thresholding techniques which are used are local thresholding and global thresholding.

Global Thresholding

Global thresholding described is successful in highly controlled environments. One of the areas in which this often is possible is in industrial inspection applications, where control of the illumination usually is feasible.

The basic global threshold, T, is calculated as follows:

(1) Select an initial estimate for T (typically the average grey level in the image)

(2) Segment the image using T to produce two groups of pixels: G_1 consisting of pixels with grey levels $>T$ and G_2 consisting pixels with grey levels $\leq T$

(3) Compute the average grey levels of pixels in G_1 to give μ_1 and G_2 to give μ_2

(4) Compute a new threshold value.

$$T = 1/2\ (\mu_1 + \mu_2)$$

(5) Repeat steps 2 – 4 until the difference in T in successive iterations is less than a predefined limit $T = \infty$.

Local Thresholding

Images having uneven illumination make it difficult to segment using global thresholding, this approach is to divide the original image into sub images and use the above said thresholding process to each of the sub images [5].

Local Enhancement

Histogram processing methods [6], [7] are global processing, in the sense that pixels are modified by a transformation function based on the gray-level content of an entire image. Sometimes, we may need to enhance details over small areas in an image, which is called a local enhancement. Original image say (slightly blurred to reduce noise).Global histogram equalization (enhance noise & slightly increase contrast but the construction is not change. Local histogram equalization using 7x7 neighborhoods (reveals the small squares inside larger ones of the original image. Define a square or rectangular neighborhood and move the center of this area from pixel to pixel. At each location, the histogram of the points in the neighborhood is computed and either histogram equalization or histogram specification transformation function is obtained. Another approach used to reduce computation is to utilize non-overlapping regions, but it usually produces an undesirable checkerboard effect.

When we use the local enhancement technique, it reveals the small areas. Note also the finer noise texture is resulted by the local processing using relatively small neighborhoods.

We calculate mean and variance for enhancement purposes. The global mean and variance are measured over an entire image and are useful for gross adjustments of overall intensity and contrast. A much more powerful use of these two measures is in local enhancement, where the local mean and variance are used as the basis for making changes that depend on he image characteristics in a predefined region about each pixel in the image. The local mean is a measure of average gray level in neighborhood and the variance is a measure of contrast in neighborhood. If the problem is to enhance dark areas while leaving the light areas as unchanged as they don't require any enhancement. We can use the concepts presented in this section to formulate an enhancement method that can tell the difference between dark and light and at the same time capable of enhancing only the dark areas. A measure of whether an area is relatively light or dark at appoint is to compare the local average gray level to the average image gray level.

1.4 Edge Detection

Edge detection refers to the process of identifying and locating sharp discontinuities in an image. The discontinuities are abrupt changes in pixel intensity which characterize boundaries of objects in a scene. Classical methods of edge detection involve convolving the image with an operator (a 2-D filter), which is constructed to be sensitive to large gradients in the image while returning values of zero in uniform regions. There is an extremely large number of edge detection operators available [8], each designed to be sensitive to certain types of edges. Variables involved in the selection of an edge detection operator include:

- **Edge orientation:** The geometry of the operator determines a characteristic direction in which it is most sensitive to edges. Operators can be optimized to look for horizontal, vertical, or diagonal edges.
- **Noise environment:** Edge detection is difficult in noisy images, since both the noise and the edges contain high-frequency content. Attempts to reduce the noise result in blurred and distorted edges. Operators used on noisy images are typically larger in scope, so they can average enough data to discount localized noisy pixels. This results in less accurate localization of the detected edges.
- **Edge structure:** Not all edges involve a step change in intensity. Effects such as refraction or poor focus can result in objects with boundaries defined by a gradual change in intensity. The operator needs to be chosen to be responsive to such a gradual change in those cases. Newer wavelet-based techniques actually characterize the nature of the transition for each edge in order to

distinguish, for example, edges associated with hair from edges associated with a face.

There are many ways to perform edge detection. However, the majority of different methods may be grouped into two categories [9]:

- **Gradient:** The gradient method detects the edges by looking for the maximum and minimum in the first derivative of the image.
- **Laplacian:** The Laplacian method searches for zero crossings in the second derivative of the image to find edges. An edge has the one-dimensional shape of a ramp and calculating the derivative of the image can highlight its location. Suppose we have the following signal, with an edge shown by the jump in intensity below.

Suppose we have the following signal, with an edge shown by the jump in intensity below.

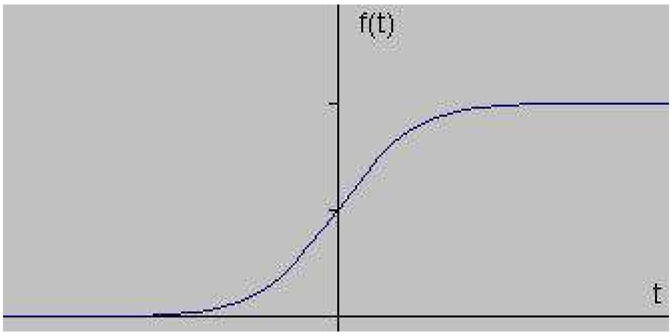

Fig. 1.1. Sample signal with an edge

If we take the gradient of this signal (which, in one dimension, is just the first derivative with respect to t) we get the following.

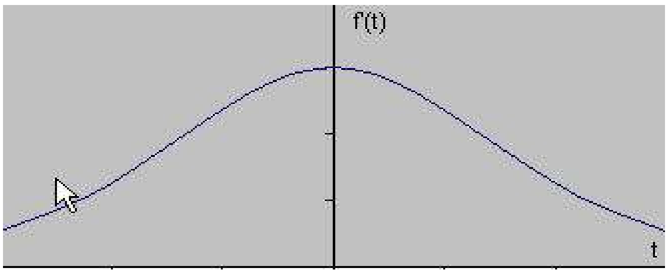

Fig. 1.2. First derivative of the signal

Clearly, the derivative shows a maximum located at the center of the edge in the original signal. This method of locating an edge is characteristic of the "gradient filter" family of edge detection filters and includes the Sobel method. A pixel location is declared an edge location if the value of the gradient exceeds some threshold. As mentioned before, edges will have higher pixel intensity values than those surrounding it. So once a threshold is set, you can compare the gradient value to the threshold value and detect an edge whenever the threshold is exceeded. Furthermore, when the first derivative is at a maximum, the second derivative is zero. As a result, another alternative to finding the location of an edge is to locate the zeros in the second derivative. This method is known as the Laplacian and the second derivative of the signal is shown below.

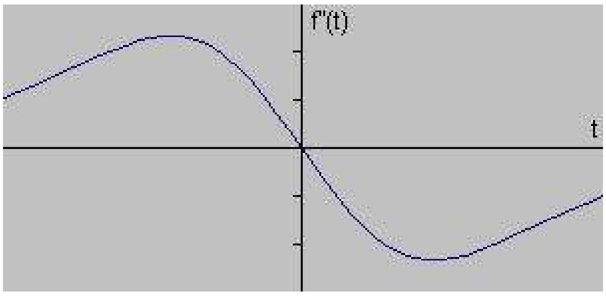

Fig. 1.3. Second derivative of the signal

1.4.1 Edge Detection Techniques

Sobel Operator

The operator consists of a pair of 3×3 convolution kernels as shown in Figure 1. One kernel is simply the other rotated by 90°.

-1	0	+1
-2	0	+2
-1	0	+1

Gx

+1	+2	+1
0	0	0
-1	-2	-1

Gy

These kernels are designed to respond maximally to edges running vertically and horizontally relative to the pixel grid, one kernel for each of the two perpendicular orientations. The kernels can be applied separately to the input image, to produce separate measurements of the gradient component in each orientation (call these *Gx* and *Gy*). These can then be combined together to find the absolute magnitude of the gradient at each point and the orientation of that gradient. The gradient magnitude is given by:

$$|G| = \sqrt{Gx^2 + Gy^2}$$

Typically, an approximate magnitude is computed using:

$$|G| = |Gx| + |Gy|$$

which is much faster to compute.

The angle of orientation of the edge (relative to the pixel grid) giving rise to the spatial gradient is given by:

$$\theta = \arctan(Gy / Gx)$$

Robert's cross operator

The Roberts Cross operator performs a simple, quick to compute, 2-D spatial gradient measurement on an image. Pixel values at each point in the output represent the estimated absolute magnitude of the spatial gradient of the input image at that point. The operator consists of a pair of 2×2 convolution kernels as shown in Figure. One kernel is simply the other rotated by 90°. This is very similar to the Sobel operator.

+1	0
0	-1

Gx

0	+1
-1	0

Gy

These kernels are designed to respond maximally to edges running at 45° to the pixel grid, one kernel for each of the two perpendicular orientations. The kernels can be applied separately to the input image, to produce separate measurements of the gradient component in each orientation (call these *Gx* and *Gy*). These can then be combined together to find the absolute magnitude of the gradient at each point and the orientation of that gradient. The gradient magnitude is given by:

$$|G| = \sqrt{Gx^2 + Gy^2}$$

although typically, an approximate magnitude is computed using:

$$|G| = |Gx| + |Gy|$$

which is much faster to compute.
The angle of orientation of the edge giving rise to the spatial gradient (relative to the pixel grid orientation) is given by:

$$\theta = \arctan(Gy / Gx) - 3\pi / 4$$

Prewitt's operator

Prewitt operator is similar to the Sobel operator and is used for detecting vertical and horizontal edges in images.

$$h_1 = \begin{bmatrix} 1 & 1 & 1 \\ 0 & 0 & 0 \\ -1 & -1 & -1 \end{bmatrix} \qquad h_3 = \begin{bmatrix} -1 & 0 & 1 \\ -1 & 0 & 1 \\ -1 & 0 & 1 \end{bmatrix}$$

Laplacian of Gaussian

The Laplacian is a 2-D isotropic measure of the 2nd spatial derivative of an image. The Laplacian of an image highlights regions of rapid intensity change and is therefore often used for edge detection. The Laplacian is often applied to an image that has first been smoothed with something approximating a Gaussian Smoothing filter in order to reduce its sensitivity to noise. The operator normally takes a single graylevel image as input and produces another graylevel image as output.

The Laplacian *L(x,y)* of an image with pixel intensity values *I(x,y)* is given by:

$$L(x,y) = \frac{\partial^2 I}{\partial x^2} + \frac{\partial^2 I}{\partial y^2}$$

Since the input image is represented as a set of discrete pixels, we have to find a discrete convolution kernel that can approximate the second derivatives in the definition of the Laplacian. Three commonly used small kernels are shown below:

0	1	0
1	−4	1
0	1	0

1	1	1
1	−8	1
1	1	1

−1	2	−1
2	−4	2
−1	2	−1

1.5 Watershed Algorithm

In gray scale mathematical morphology the watershed [10], [11] algorithm, originally proposed by Digabel and Lantuejoul is the method of choice for image segmentation. The intuitive idea underlying this method comes from geography: It regards the gradient magnitude image as a landscape where the intensity values correspond to the elevation. Areas where a raindrop would drain to the same minimum are denoted as catchment basins, and the lines separating adjacent catchment basins are called watersheds.

Steps of watershed algorithm are as follows:-

1) Remove some of the weakest edges (e.g. due to noise)

2) Compute the gradient map of original image.

3) Compute the maximum value (MAX) of gradient map.

4) Select the appropriate drowning threshold of watershed method: DT=MAX* l/n.

5) For each pixel, we consider its 8-neighbor. If the value of current pixel and its neighbor is smaller DT, we merge current pixel with its neighbor.

6) Merge the smaller regions using the Fisher criterion (e.g. the pixel number of region40).

From above, we know the output of watershed algorithm is an over-segmentation of original image, and it is very important to select drowning threshold DT, which determines the region numbers of the segmentation.

1.6 Active Contour Method

Active Contour [11], [12] Method besides challenges due to imaging noise and partial volume effects, the similarity in intensity and texture between neighboring structures complicates the task of identifying distinct boundaries between the structures. So the active contour method was introduced which developed the concept of shape contours .When evolving shape contours, the interaction consists of modeling the "forces" of attraction, repulsion, and competition by taking into account the relationship between object contours and their shape estimates.

The morphological operations [13] are to be performed on grey scale itself for required transformation which leads to uniformity factor.

The process of segmentation results in an image of the same size as the original but consists of only two levels to distinguish between the elements of interest and background. The segmented images are also known as Binary Images. In our case the segmented image of the membrane filter beads results in an image with black background with white beads. The white beads are elements of interest which are to be extracted and their areas are to be calculated for checking the uniformity in the polymer beads of the membrane filter.

The basic idea in active contour models or snakes is to evolve a curve, subject to constraints from a given image, in order to detect objects in that image. For instance, starting with a curve around the object to be detected, the curve moves toward its interior normal and has to stop on the boundary of the object.

1.7 Circular Hough Transform

The Hough Transform (HT) [14] and several modified versions have been recognized as robust techniques for curve detection. This method can detect object even polluted by noise. The CHT is one of the modified versions of the HT. The CHT aims to find circular patterns within an image. The CHT is used to transform a set of feature points in the image space into a set of accumulated votes in a parameter space. Then, for each feature point, votes are accumulated in an accumulator array for all parameter combinations. The array elements that contain the highest number of votes indicate the presence of the shape.

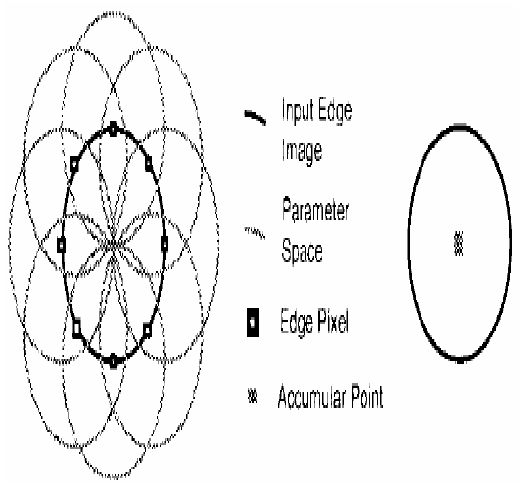

Fig. 1.4. A Typical Circle detection using Hough Transform

The black circles in Fig.1.4 indicate a set edge points within the image. Each edge point contributes a circle of radius R to an output accumulator space indicated by the grey circles. The output accumulator space has a peak where these contributed circles overlap at the center of the original circle. Modification to the CHT has been widely implemented to either increase the detection rate or reduce its computational complexity

CHAPTER 2

LITERATURE REVIEW

Malik Sikandar Hayat Khiyal, et al. [15] present a technique to reduce the deficiencies of watershed algorithm. We know that the Watershed algorithm can generate over segmentation or under segmentation on badly contrast images. Good result of watershed segmentation entirely relay on the image contrast and the image contrast may be degraded during image acquisition. Therefore, a preprocessing step is performed on input images using Random Walk method. This step enhances the contrast of the input image so that the gradient of the image is strong enough to properly segment the image by using the watershed. After preprocessing step the gradient of the image is finding by converting the input image to grey scale. And this gradient of image is used as the input the image. The results show the improvement in the segmentation results using random walk.

Nayer M. Wanas, et al. [16] provide several local and global feature selection methods. The usage of Standard Deviation (STD) and Maximum Deviation (MD) as globalization schemes is also suggested. They provide a comparative study among fourteen thresholding techniques using different scoring methods and benchmark datasets of diverse nature.

T.Lampert and S. O'Keefe [17] propose an active contour framework for spectrogram track detection. A potential energy is proposed which results in feature extraction at a signal-to-noise ratio (SNR) of 0.5dB. This is also achievable in real-time through complexity analysis.

Raman Maini and Dr. Himanshu Aggarwal [18] present the comparative analysis of various Image Edge Detection techniques and it has been shown that the Canny's edge detection algorithm performs better than all these operators under almost all scenarios**.** Evaluation of the images show that under noisy conditions Canny, LoG (Laplacian of Gaussian), Robert, Prewitt, Sobel exhibit better performance, respectively.

Jianbo Shi and Jitendra Malik [19] propose a novel approach for solving the perceptual grouping problem in vision. Rather than focusing on local features and their consistencies in the image data, this approach aims at extracting the global impression of an image. The image segmentation is treated as a graph partitioning problem and a novel global criterion, the normalized cut, is proposed for segmenting the graph. The normalized cut criterion measures both the total dissimilarity between the different groups as well as the total similarity within the groups. An efficient computational technique based on a generalized eigen value problem is used to optimize this criterion.

Marcin Smereka and Ignacy Duleba [20] propose a practical modification of the Hough transform that improves the detection of low-contrast circular objects. The original circular Hough transform and its numerous modifications are discussed and compared in order to improve both the efficiency and computational complexity of the algorithm. Medical images are selected to verify the algorithm.

Wei Liu and YuHong Zhao [21] propose a feasible image enhancement method for crystal identification in crystallization image by using histogram equalization and Laplacian mask algorithm sequentially. The effect of the crystal image can be improved and the crystals can be identified more easily and exactly.

Dipti Deodhare, NNR Ranga Suri and R. Amit [22] discuss the form image registration technique and the image masking and image improvement techniques implemented in the system as part of the character image extraction process. These techniques help in preparing the input character image for the neural networks-based classifiers and go a long way in improving overall system accuracy.

Thomas Heseltine,Nick Pears and Jim Austin [23] present a range of image processing techniques as potential pre-processing steps, which attempt to improve the performance of the eigenface method of face recognition.Verification tests are carried out by applying thresholds to gather false acceptance rate (FAR) and false rejection rate (FRR) results from a data set comprised of images that present typical difficulties when attempting recognition, such as strong variations in lighting direction and intensity, partially covered faces and changes in facial expression. Results are compared using the equal error rate (EER), which is the error rate when FAR is equal to FRR. We determine the most successful methods of image processing to be used with eigenface based face recognition, in application areas such as security, surveillance, data compression and archive searching.

Gloria Bueno, et al. [24] present a comparative study between different colour models (RGB, HSI) applied to a very large microscopic image analysis. Such analysis of different colour models is needed in order to carry out a successful detection and therefore a classification of different regions of interest (ROIs) within the image. This, in turn, allows both distinguishing possible ROIs and retrieving their proper colour for further ROI analysis. This analysis is not commonly done in many biomedical applications that deal with colour images.

Konstantinos N. Plataniotis et al. [25] discuss new adaptive filters for color image processing. The new filters utilize Bayesian techniques and nonparametric methodologies to adapt to local data in the color image. Simulation studies indicate that the new filters are computationally attractive and have excellent performance.

Mehmet, Gurell and Levent Onural [26] describe a class of adaptive directional image smoothing filters based on generalized Gaussian distributions. The gray level distribution around a pixel of an image usually tends to be more coherent in some directions compared to other directions. The idea of adaptive directional filtering is to estimate the direction of higher coherence around each pixel location and then to employ a window which approximates a line segment in that direction. A measure of spread for the pixel values is proposed based on the maximum likelihood estimate of a scale parameter involved in the generalized Gaussian distribution. Hence, the details of the image may be preserved while maintaining a satisfactory level of noise suppression performance.

Chih-Cheng Hung [27] propose an improvement on the gradient inverse weighted (GIW) filter for digital image smoothing. The selection of the optimal homogeneous neighboring pixels for spatial smoothing is achieved through the integration of directional masks and the adaptation of the selected subregion based on local statistics of the image data. This adaptive approach is effective in smoothing images containing complex-shaped objects such as remotely sensed imagery.

Masoud Nosrati et al. [28] introduce a method by using 4 steps to extract circular shapes from impulse noisy backgrounds. First step is applying median filter to disappear "salt and pepper" noise. This step causes edge smoothing. So, as the second step, a laplacian sharpening spatial filter should be applied. It highlights fine details and enhances the blurred edges. Using these two steps sequentially causes noise reduction in an impressive way. Third step is using Canny edge detection for segmenting the image. Finally, forth step is applying Circular Hough Transform (CHT) for detecting the circles in image.

Saif D. Salman & Ahmed A. Bahrani [29] present a new method of tumor line detection and segmentation is used to separate the abnormal from the normal surrounding tissue to get a real identification of involved and noninvolved area that help the surgeon to distinguish the involved area precisely. The method used is watershed method and image processing by using MatLab 7.1 to detect the tumor boundaries in MRI and CT image for different cases. The result in this study is very clear for physician to distinguish the area of tumor for surgical planning.

CHAPTER 3

IMAGE PREPROCESSING TECHNIQUES

The Membrane Filter (MF) Technique was introduced in the late 1950s as an alternative to the Most Probable Number (MPN) procedure for microbiological analysis of water samples.

The MF Technique offers the advantage of isolating discrete colonies of bacteria, whereas the MPN procedure only indicates the presence or absence of an approximate number or organisms (indicated by turbidity in test tubes).

In membrane filtration, a solute is passed through a semi-permeable membrane. The membrane's permeability is determined by the size of the pores in the membrane, and it will act as a barrier to particles which are larger than the pores, while the rest of the solute can pass freely through the membrane.

The result is a cleaned and filtered fluid on one side of the membrane, with the contaminated solute on the other side.

Nano filtration, ultra filtration, microfiltration, and reverse osmosis are all membrane filtration techniques. In all cases, the size of the pores has to be carefully calculated to exclude undesirable particles, and the size of the membrane has to be designed for optimal operating efficiency.

Membranes are also prone to clogging as the pores slowly fill with trapped particles, which means that the system must provide accommodations for easy cleaning and maintenance so that it can be kept in good working order.

Many membrane filtration systems are designed for industrial uses. One of the big advantages to such a system is that it does not require the use of chemicals or additives, which cuts down on operating costs.

Additionally, membrane filtration requires minimal energy, and it can in fact be designed to run on almost no energy, with a pressurized system which takes advantage of gravity and forces the solute through the membrane at a steady rate. Successive membrane filtration, in which the solute passes through a series of membranes, is very popular. In this approach, the pores get progressively smaller, removing more and more impurities from the fluid.

This technique reduces clogging of the system as the solute is slowly filtered, and it carries the added advantage of fitting into a compact space, because the membranes can all be very small and still work efficiently.

Municipal water treatment plants monitor drinking, waste, and surface water for the presence of coli form bacteria by the MF Technique. The key organism monitored in water treatment facilities is *E. coli*. The U.S. EPA considers this organism the leading indicator of fecal contamination.

In addition to its use by government labs for monitoring drinking water, the MF Technique is also used for microbial monitoring in the pharmaceutical, cosmetics, electronics, and food and beverage industries.

The MF Technique is used in these industrial labs to monitor the presence of microorganisms in process waters and final product.

The pharmaceutical and cosmetics industries typically focus on monitoring their process water for *Pseudomonas* species.

The electronics industry monitors for any and all microorganisms because they must keep their process water free from even the smallest organisms. Microbial monitoring in the food and beverage industry typically employs several types of techniques because of the variety of samples that are encountered. Beverage samples can typically be monitored for microorganisms by the MF Technique, but when solid samples cannot be liquefied, alternative methods must be used.

Fig. 3.1. Membrane filters

3.1 Bacteriological Analysis by the Membrane Filter Technique

The membrane filter technique is now considered the preferred method for the bacteriological analysis of water , unless the turbidity of the sample is sufficient to clog the pores of the filter.

It permits the examination of a larger volume of sample than does the multiple-tube technique, a direct count of the bacteria in the water, rather than a statistical approximation and completion of the test in 24 hours, whereas the multiple –tube method usually requires 48-72 hours for a confirmed test (longer for a completed test).

The basic principles involved in the membrane-filter method of determining the presence and number of coli form organisms in a given quantity of water are as follows:

(1) A given quantity of water is filtered through a porous disk of polyester cellulose acetate. The porosity of the filter is 79 percent ,and the size of the pores is 0.45 microns. Since coli form bacteria are from 1 to 4 microns in length, they are retained on the filter when the water passes through.

(2) Because the pores of the filter are so small,the water will not pass through the filter by gravity.

Therefore, a vaccum source must be available to enable the water to penetrate the filter. In the laboratory, a hydrosol with a power vaccum source is used. In the field,a hand-operated vaccum pump is used.

(3) After the water sample has been filtered,the filter is incubated at 35ºC for 22-24 hours in contact with M-Endo medium in a petri dish.

This culture medium is favorable to the growth of coli form bacteria, but it inhibits the growth of other types of bacteria.

(4) This gives it a selective characteristic. Although a few other types of bacterial colonies may develop on the culture medium ,the coli form bacteria will reproduce better, forming readily identifiable colonies. Colonies may be counted using a low power microscope or a simple hand magnifier.

3.2 Membrane Filtration for Water and Wastewater

Membrane filtration [30], widely used in chemical and biotechnology processes, is already established as a valuable means of filtering and cleaning wastewater and industrial process water. Membrane filtration, widely used in chemical and biotechnology processes, is already established as a valuable means of filtering and cleaning wastewater and industrial process water. More recently, tubular and spiral membrane plants have begun to be used to filter impurities from drinking water in regions where conventional treatment proves to be uneconomical. Although there are a number of different methods of filtration that incorporate membrane technology, the most mature is pressure driven membrane filtration.

3.3 Spatial and Gray-Level Resolution

Sampling is the principal factor determining the spatial resolution of an image. Basically, spatial resolution is the smallest discernible detail in an image. A widely used definition of resolution is simply the smallest number of discernible line pairs per unit distance. Gray-level resolution similarly refers to the smallest discernible change in gray level, but, measuring discernible changes in gray level is a highly subjective process. We have considerable discretion regarding the number of samples used to generate a digital image, but this is not true for the number of gray levels.

3.3.1 Zooming and Shrinking Digital Images

This topic is related to image sampling and quantization because zooming may be viewed as over sampling, while shrinking may be viewed as under sampling. The key difference between these two operations and sampling and quantizing an original continuous image is that zooming and shrinking are applied to a digital image [31]. Zooming requires two steps:-

1) The creation of new pixel locations
2) The assignment of gray levels to those new locations.

3.3.2 Some Basic Relationships Between Pixels

Adjacency, Connectivity, Regions, and Boundaries

Connectivity between pixels is a fundamental concept that simplifies the definition of numerous digital image concepts, such as regions and boundaries. To establish if two pixels are connected, it must be determined if they are neighbors and if their gray levels satisfy a specified criterion of similarity in a binary image with values 0 and 1, two pixels may be 4-neighbors, but they are said to be connected only if they have the same value.

Visual evaluation of image quality is a highly subjective process, thus making the definition of a "good image" an elusive standard by which to compare algorithm performance. When the problem is one of processing images for machine perception, the evaluation task is somewhat easier.

For example, in dealing with a character recognition application, and leaving aside other issues such as computational requirements, the best image processing method would be the one yielding the best machine recognition results.

However, even in situations when a clear-cut criterion of performance can be imposed on the problem, a certain amount of trial and error usually is required before a particular image enhancement approach is selected.

3.3.3 Some Basic Gray Level Transformations

We begin the study of image enhancement techniques by discussing gray-level transformation functions. These are among the simplest of all image enhancement techniques. Since we are dealing with digital quantities, values of the transformation function typically are stored in a one-dimensional array.

3.3.4 Gray-level slicing

Highlighting a specific range of gray levels in an image often is desired. Applications include enhancing features such as masses of water in satellite imagery and enhancing flaws in X-ray images.

There are several ways of doing level slicing, but most of them are variations of two basic themes.

1) One approach is to display a high value for all gray levels in the range of interest and a low value for all other gray levels.

2) The second approach, brightens the desired range of gray levels but preserves the background and gray-level tonalities in the image.

3.3.5 Image Subtraction

The difference between two images is obtained by computing the difference between all pairs of corresponding pixels.

The key usefulness of subtraction [32] is the enhancement of differences between images. Image Averaging

Consider a noisy image $g(x, y)$ formed by the addition of noise $V(x, y)$ to an

original image that is,

$$g(x, y) = f(x, y) + V(x, y)$$

The objective of the following procedure is to reduce the noise content by adding a set of noisy images, $\{g_i(x, y)\}$.

If the noise satisfies the constraints just stated, it can be shown that if an image $g(x, y)$ is formed by averaging K different noisy images,

$$\bar{g}(x, y) = \frac{1}{K}\sum_{i=1}^{K} g_i(x, y)$$

and

$$E\{g(x, y)\} = f(x, y)$$

$$\sigma^2_{\bar{g}_i(x,y)} = \frac{1}{K}\sigma^2_{\eta(x,y)}$$

where $E\{g(x, y)\}$ is the expected value of g,

The standard deviation at any point in the average image is

$$\sigma_{\bar{g}(x,y)} = \frac{1}{\sqrt{K}}\sigma_{\eta(x,y)}$$

As K increases,the variability (noise) of the pixel values at each location *(x,y)* decreases. Because $E\{g(x,y)\} = f(x,y)$, this means that *g(x, y)* approaches *f(x, y)* as the number of noisy images used in the averaging process increases. In practice, the images $g_i(x,y)$ must be registered (aligned) in order to avoid the introduction of blurring and other artifacts in the output image.

An important application of image averaging is in the field of astronomy, where imaging with very low light levels is routine, causing sensor noise frequently to render single images virtually useless for analysis.

3.4 Image Preprocessing Filters

For noise reduction and other image preprocessing steps number of image preprocessing filters are used. Some of them are given below.

3.4.1 Smoothing Spatial Filters

Smoothing filters are used for blurring and for noise reduction. Blurring is used in preprocessing steps, such as removal of small details from an image prior to (large) object extraction, and bridging of small gaps in lines or curves. Noise reduction can be accomplished by blurring with a linear filter and also by non- linear filtering.

3.4.2 Smoothing Linear Filters

The output (response) of a smoothing, linear spatial filter is simply the average of the pixels contained in the neighborhood of the filter mask. These filters sometimes are called averaging filters [33].

The idea behind smoothing filters is straightforward. By replacing the value of every pixel in an image by the average of the gray levels in the neighborhood defined by the filter mask, this process results in an image with reduced "sharp" transitions in gray levels. Because random noise typically consists of sharp transitions in gray levels, the most obvious application of smoothing is noise reduction.

However, edges (which almost always are desirable features of an image) also are characterized by sharp transitions in gray levels, so averaging filters have the undesirable side effect that they blur edges. Another application of this type of process includes the smoothing of false contours that result from using an insufficient number of gray levels.

3.4.3 Sharpening Spatial Filters

The principal objective of sharpening is to highlight fine detail in an image or to enhance detail that has been blurred, either in error or as a natural effect of a particular method of image acquisition.

Uses of image sharpening vary and include applications ranging from electronic printing and medical imaging to industrial inspection and autonomous guidance in military systems.

Image blurring could be accomplished in the spatial domain by pixel averaging in a neighborhood. Since averaging is analogous to integration, it is logical to conclude that sharpening could be accomplished by spatial differentiation. This, in fact, is the case, and the discussion in this section deals with various ways of defining and implementing operators for sharpening by digital differentiation.

Fundamentally, the strength of the response of a derivative operator is proportional to the degree of discontinuity of the image at the point at which the operator is applied. Thus, image differentiation enhances edges and other discontinuities (such as noise) and deemphasizes areas with slowly varying gray-level values.

The derivatives of a digital function are defined in terms of differences. There are various ways to define these differences. However, we require that any definition we use for a first derivative

A) must be zero in flat segments (areas of constant gray-level values);

B) must be nonzero at the onset of a gray-level step or ramp;

C) must be nonzero along ramps.

Similarly, any definition of a second derivative

A) must be zero in flat areas;

B) must be nonzero at the onset and end of a gray-level step or ramp;

C) must be zero along ramps of constant slope. Since we are dealing with digital quantities whose values are finite, the maximum possible gray-level change also is finite, and the shortest distance over which that change can occur is between adjacent pixels.

Let us consider the properties of the first and second derivatives as we traverse the profile from left to right. First, we note that the first-order derivative is nonzero along the entire ramp, while the second-order derivative is nonzero only at the onset and end of the ramp. Because edges in an image resemble this type of transition, we conclude that first-order derivatives produce "thick" edges and second-order derivatives, much finer ones. Next we encounter the isolated noise point. Here, the response at and around the point is much stronger for the second- than for the first-order derivative. Of course, this is not unexpected. A second-order derivative is much more aggressive than a first-order derivative in enhancing sharp changes [34].
Thus, we can expect a second-order derivative to enhance fine detail (including noise) much more than a first-order derivative. The thin line is a fine detail, and we see essentially the same difference between the two derivatives. If the maximum gray level of the line had been the same as the isolated point, the response of the second derivative would have been stronger for the latter.
Finally, in this case, the response of the two derivatives is the same at the gray-level step (in most cases when the transition into a step is not from zero, the second derivative will be weaker). We also note that the second derivative has a transition from positive back to negative. In an image, this shows as a thin double line. This "double-edge" effect is an issue that will be important , where we use derivatives for edge detection.

It is of interest also to note that if the gray level of the thin line had been the same as the step, the response of the second derivative would have been stronger for the line than for the step.

We also note of second-order derivatives that, for similar changes in gray-level values in an image, their response is stronger to a line than to a step, and to a point than to a line.

In most applications, the second derivative is better suited than the first derivative for image enhancement because of the ability of the former to enhance fine detail. For this, and for reasons of simpler implementation and extensions, we will focus attention initially on uses of the second derivative for enhancement.

3.5 Comparing the response between first and second-order derivatives

First Order Derivative	Second Order Derivative
a) First-order derivatives generally produce thicker edges in an image.	a) Second-order derivatives have a stronger response to fine detail, such as thin lines and isolated points.
b) First- order derivatives generally have a stronger response to a gray-level step	b) Second-order derivatives produce a double response at step changes in gray

3.6 Image Enhancement in the Frequency Domain

Low frequencies in the Fourier transform are responsible for the general gray-level appearance of an image over smooth areas, while high frequencies are responsible for detail, such as edges and noise. These ideas are discussed in more detail in the sections that follow, but it will be instructive to complement our illustration of the notch filter with an example of filters in these other two categories.

A filter that attenuates high frequencies while passing low frequencies is called a low pass filter.

A filter that has the opposite characteristic is appropriately called a high pass filter.

We would expect a low pass-filtered image to have less sharp detail than the original because the high frequencies have been attenuated. Similarly, a high pass-filtered image would have less gray level variations in smooth areas and emphasized transitional (e.g., edge) gray-level detail. Such an image will appear sharper.

Low pass filtering is a staple in the printing and publishing industry, where it is used for numerous preprocessing functions, including unsharp masking. Cosmetic processing is another use of low pass filtering prior to printing.

3.6.1 Sharpening Frequency Domain Filters

An image can be blurred by attenuating the high-frequency components of its Fourier transform. Because edges and other abrupt changes in gray levels are associated with high-frequency components, image sharpening can be achieved in the frequency domain by a high pass filtering process, which attenuates the low-frequency components without disturbing high-frequency information in the Fourier transform.

As intended, this filter is the opposite of the ideal low- pass filter ILPF in the sense that it sets to zero all frequencies inside a circle of radius Do while passing, without attenuation, all frequencies outside the circle. As in the case of the ideal low-pass filter, the ideal high pass filter IHPF is not physically realizable with electronic components.

Our work is related to granular image processing to segment granules in different domains.

A) One such related problem is of automatic cell segmentation [35].Cell image segmentation is a necessary first step of many automated biomedical image-processing procedures. There certainly has been much research in the area. To this, a new method has been added, which automatically extracts cells from microscopic imagery, and does so in two phases. Phase 1 uses iterated thresholding to identify and mark foreground objects or `blobs' with an overall accuracy of >97%. Phase 2 of the method uses a novel genetic algorithms-based ellipse detection algorithm to identify cells, quickly and reliably. The mechanism, as a whole, has an accuracy rate >96% and takes <1 min (given our specific hardware configuration) to operate on a microscopic image.
Image segmentation is the first step towards image understanding and image analysis, accurate cell segmentation is crucially important to guarantee correct results in computer-assisted microscopy.

There are two popular methods for cell segmentations [36] : ellipse fitting and the watershed transform.

Ellipse fitting [37] is an attractive method for segmenting circle-like or ellipse-like objects. However, it requires robust contour pre-processing.

i) Producing of contour segments

After preprocessing, the canny edge detector extracts the contour points are liked by an 8-neighbors' connection . The connected points are set as contour segments.

ii) Ellipse fitting algorithm

The direct least square ellipse fitting method [37] is applied on the points in each contour segment obtained instep B. This tries to fit an ellipse to the points and incorporates an ellipticity constraint into the normalization factor by minimizing the algebraic distance between the best-fit ellipse and the points, subject to the constraint 4ac-b2 = 1 . The contour segments are then classified into 3 categories: not ellipse, single cell and clustered cells. If a contour segment is not fitted by an ellipse, the contour segment is removed from the cell candidates list. If a contour segment is fitted by ellipse, the contour segment is classified as a single cell candidate or a clustered cells candidate.

B) Similar problem is coarse-to-fine particle segmentation strategy [38] to extract particles from microscopic urinary images within two stages, coarse stage and fine stage. In coarse stage, to locate particles in a wide range of images including the low contrast, the unevenly illuminated, etc, we develop 4-direction variance mapping followed by an adaptive thresholding method. Within this stage, particles are well located, but their contours fail to exactly represent their shapes and clumped particle clusters are not divided. In fine stage, combined with Canny edges, we extract desired particle contours, then an effective local maxima search algorithm based on distance map successfully separates clumped particle clusters into individual particles. This strategy is easy for implementation and its effectiveness is verified by large-scale experiments.

CHAPTER 4

RESEARCH METHODOLOGY

4.1 Main Objective of Proposed Work

The main objective of proposed work is producing a semi automated system for quality check of membrane filter using image processing. Quality of membrane filter is determined by uniformity factor of the polymer beads under test.

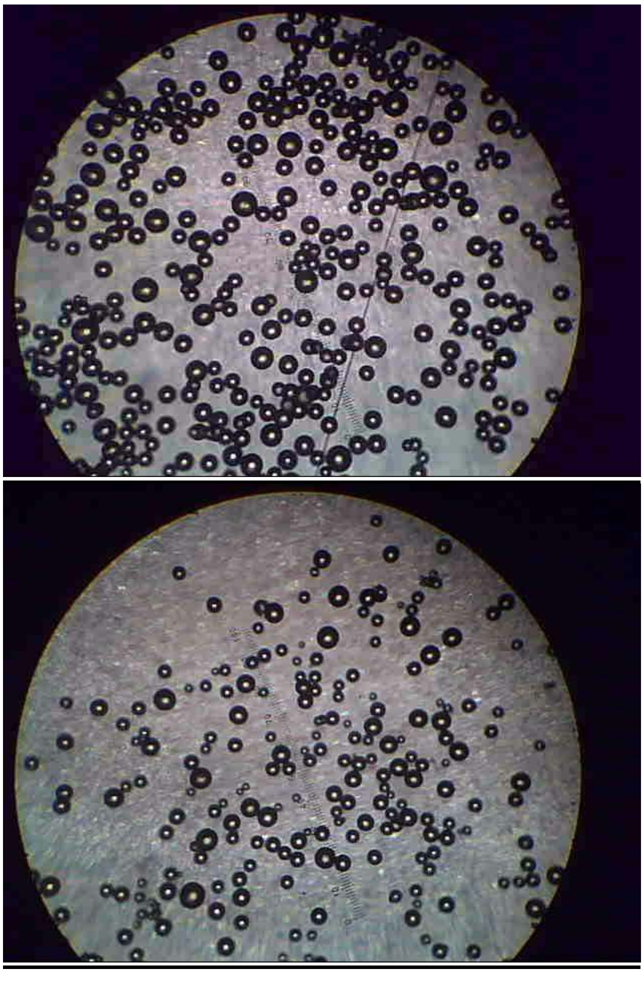

Fig. 4.1. Polymer beads 100 X microscopic images

The Image shows the Input given to the program. It shows the scattered polymer beads whose image is captured under the microscope [39].

4.2 Architecture

1) The polymer beads are spread evenly over a glass plate (1 X 1 sq inch) The input image is a microscopic image (100 X) of polymer beads present on the membrane filter.
2) Then we do preprocessing on the image to remove noise present in the image. A segmentation algorithm often needs a preprocessing step like noise smoothing to reduce the effect of undesired perturbations (artifacts) which might cause over- and under-segmentation.
3) Our next step is segmentation. The purpose of image segmentation is to decompose an image domain into a number of disjoint regions so that the features within each region have visual similarity, strong statistical correlation and reasonably good homogeneity. The preprocessed image works as the input to our segmentation algorithm [40].
4) After segmentation we can either do binary conversion of image using thresholding or grey scale conversion

    a) The goal of thresholding is to create a binary representation of the image & to discard irrelevant data and keep only the important segments of data which lie above threshold curve. It segments the digital image based on certain characteristics of pixels(for example intensity value)
    b) Grey scale dumps all the color information and leaves with very little information to work with. NTSC standard is used for the conversion to grey scale There exist several methods for segmenting gray-level images. Gray-level thresholding is one of the oldest techniques for image segmentation

5) The morphological operations are to be performed on grey scale itself for required transformation which leads to uniformity factor. The watershed transform [41] can be used to separate the clustered cells. The simple concept of watershed is that the troughs are filled with water in order to find the watershed ridge lines. However, the over-segmentation problem can occur

when we apply the watershed transform. We therefore align the object in order to reduce this problem.

6) Contour extraction, depending on the image quality & structure has two possibilities. The first one is performing image segmentation based on color & texture. If color based segmentation is not possible due to unknown information about objects, then our second way to compute the contour is direct edge detection since we need contours with a thickness of one pixel, the canny edge detector [42] is the best choice. On the one hand the methods use prior color segmentation for an indirect classification and on the other hand, an edge detector is used to obtain the contour of the objects.

The basic idea in active contour models or snakes is to evolve a curve, subject to constraints from a given image [43-46], in order to detect objects in that image. For instance, starting with a curve around the object to be detected, the curve moves toward its interior normal and has to stop on the boundary of the object.

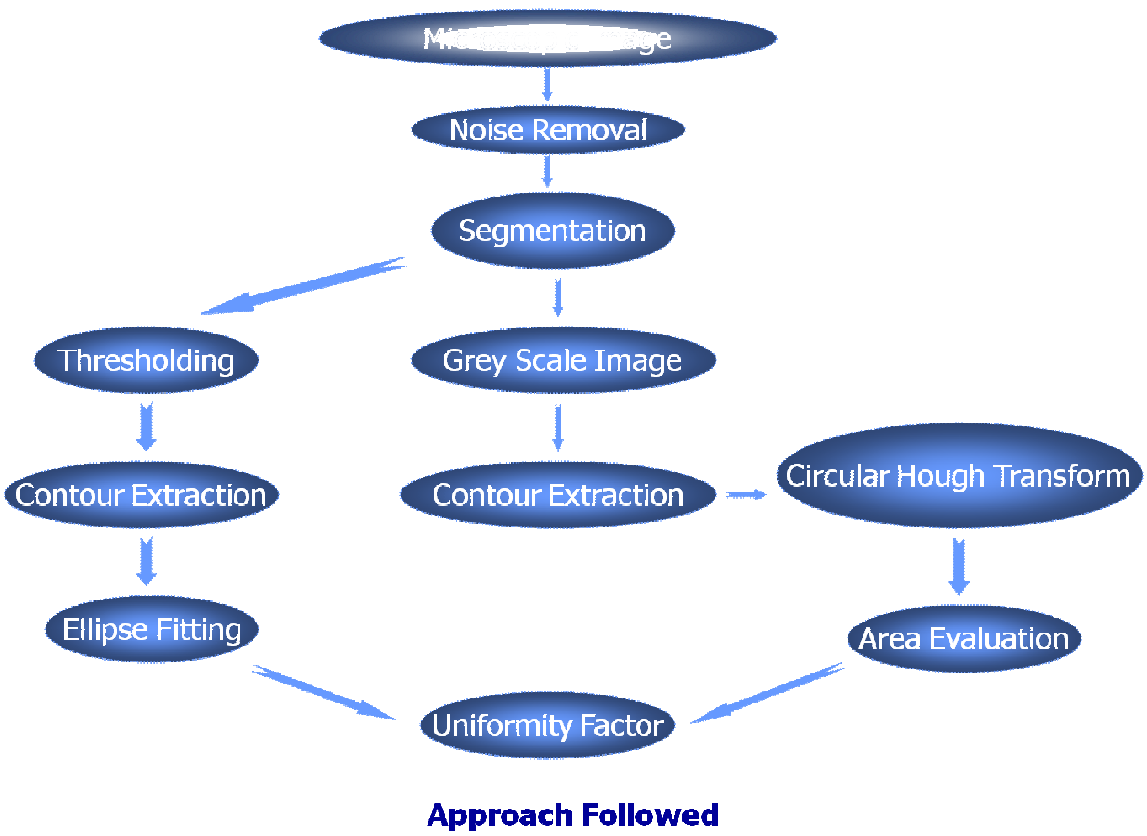

Fig. 4.2. Flow Chart showing the various steps involved

7) We now check the uniformity of polymer beads using covariance. Uniformity of beads directly affects the quality of membrane filter. Higher is the uniformity in size greater will be the quality of produced filters.

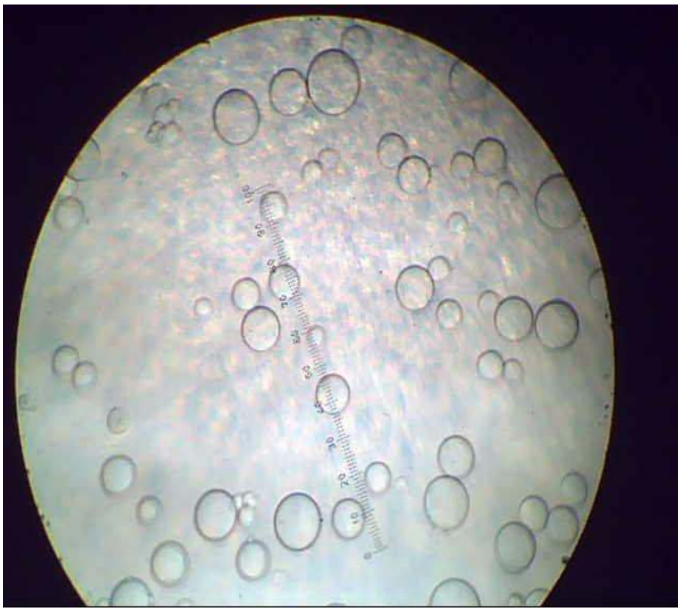

Fig 4.3: Another input image having different polymer beads

The statistical data can be obtained by processing the samples of the polymer beads. From the obtained statistical data which contains the number and area of polymer beads, the quality of the membrane filter is checked. It has been concluded from the statistical data obtained from this dissertation that if greater is the uniformity in the area of the polymer beads; better the quality of membrane filter is obtained.

4.3 Application areas

According to the quality of the membrane filter obtained it can be used for various applications within the industry, science and research. Some of applications are water recovery and recycle, fluid and water purification, capture and recovery of fluid suspended products (biological, minerals etc.), desalination of water, medical and pharmaceutical use, bacteriological examination in air and water and food and dairy industry

4.3.1 Membrane Filtration in Dairy Applications

During the last decades, the membrane filtration has been developed to a significant production process in the dairy industry. The most important dairy applications of membrane filtration are whey protein concentration, milk production (standardization) and cheese making.

As the name membrane filtration indicates, the principle of these processes is that a membrane lets different particle sizes pass through. For example in ultrafiltration (UF) of dairies large particles like fats and proteins are retained, while salts and sugars are passed through. Ultrafiltration is the most used process of membrane filtration in the dairy industry.

In milk production ultrafiltration is used for protein standardisation. Part of the milk is led to the UF plant in which it is concentrated to the desired level. The constitutes are remixed with standardized milk products.

In cheesemaking whole milk is concentrated to approximately 38-39% total solids. Then starter culture, salt, etc. are added and, depending on the type of the cheese, it is ready for moulding or for further concentration.

Whey is a liquid residue of cheese production, which contains large amounts food protein. Whey protein concentrate is gained by ultrafiltrating whey, up to 35% total solids. Also, reverse osmosis(RO) or diafiltration can be used.

Kieselguhr free Beer Membrane Filtration

Well-known beer breweries cannot afford to choose just any (new) clarification system. These systems have too big an impact on their product for that. The choice of BMF from Norit not only offers an innovative system, but also a system that has proved to be extremely reliable. Today Beer Membrane Filtration [47] is a proven technology and feasible alternative both from a quality and cost point of view. Norit offers a range of filters which are tailored into optimal filtration solutions for each individual brewery. From compact - skid mounted - units for small breweries to turn-key filter line concepts for medium-sized and large breweries.

Key benefits of Kieselguhr free Beer Membrane Filtration

Quality

Membrane technology is globally known for its quality filtrates. There are good reasons why it has proven to be the safest technology for the treatment of drinking water.

Environment, health and safety

Since membrane filtration technology can be used as a substitute for Kieselguhr filters, brewers no longer have to work with pollutant silica which are hazardous to health.

Costs

Membrane filtration is cost-competitive with other filter techniques, thanks to the efficiency of the technology, savings in environmental, health and safety measures and operational flexibility and simplicity.

Process flexibility

As membrane filtration is a fully automated process, filtration can be started up and stopped on demand. Filter replacements can be made in blocks, leaving the brewery fully operational.

Process simplicity

Because membrane filtration is safe, quick and fully automated, the filtration process at the brewery is far simpler than with other filtration methods.

Image

Breweries can use a BMF system as a demonstration of the importance they attach to environmental, health and safety issues.

CHAPTER 5

RESULTS AND DISCUSSION

The step by step process mentioned before is simulated and the results are depicted in the pages that follow.

The Input Image can be having noise, reason being scanning (conversion from Analog to Digital Format), Low lighting conditions, etc. Now the Pre-processing would include removal of Noise from the given Image so as to make it suitable for segmentation and other complex synthesis.

The Fig. below shows an Image with Noisy background:-

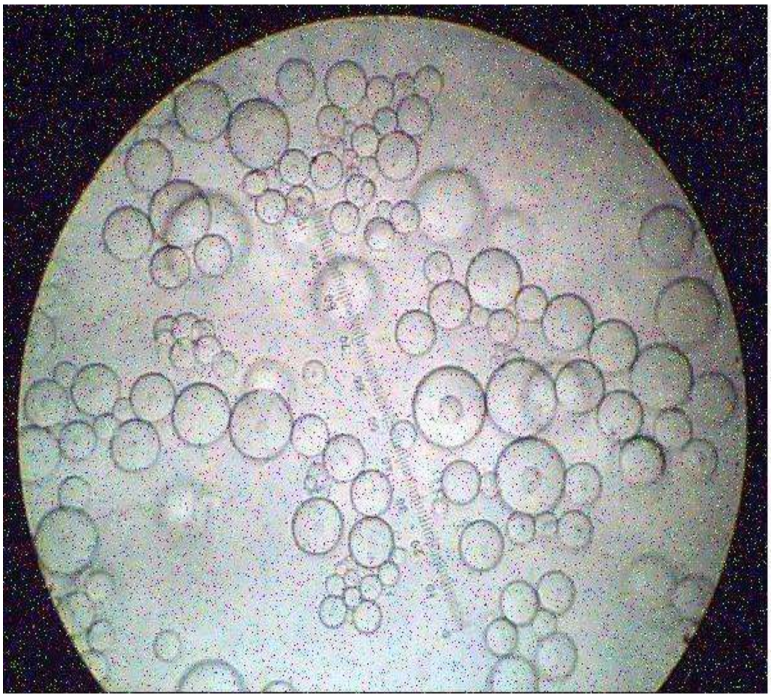

Fig. 5.1. Input Noisy Image

This is achieved by Using Filters which remove Noise. Various kinds of Filters are available e.g. Mean Filter, Median Filter, etc.

The performance of the Above said Filters was analyzed on the basis of PSNR(Peak Signal to Noise ratio) values. A relatively higher value of PSNR being desirable.

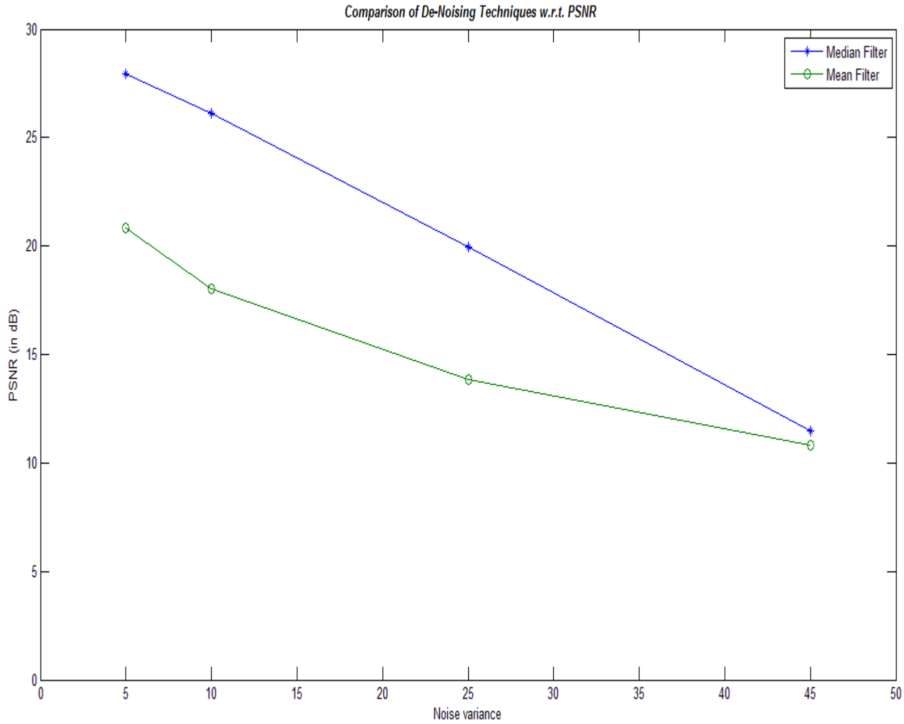

Fig. 5.2. Comparison of De-Noising Techniques w.r.t PSNR

With reference to the above graph it is clear that the MEDIAN Filter comes out with better results for varying values of Noise. Hence, that makes it the obvious choice for Noise removal.

In the Image it is clear that the background Noise has been successfully removed and the First Step of the research methodology has been completed.

Now, in cases where the Image is in RGB Format, our first and foremost consideration is to convert it into Gray Scale. Reason being the complexity of the computations is reduced as in RGB format we have to take into account three colour levels whereas with Gray Scale Format the only consideration is two levels (i.e. Either Black or White).

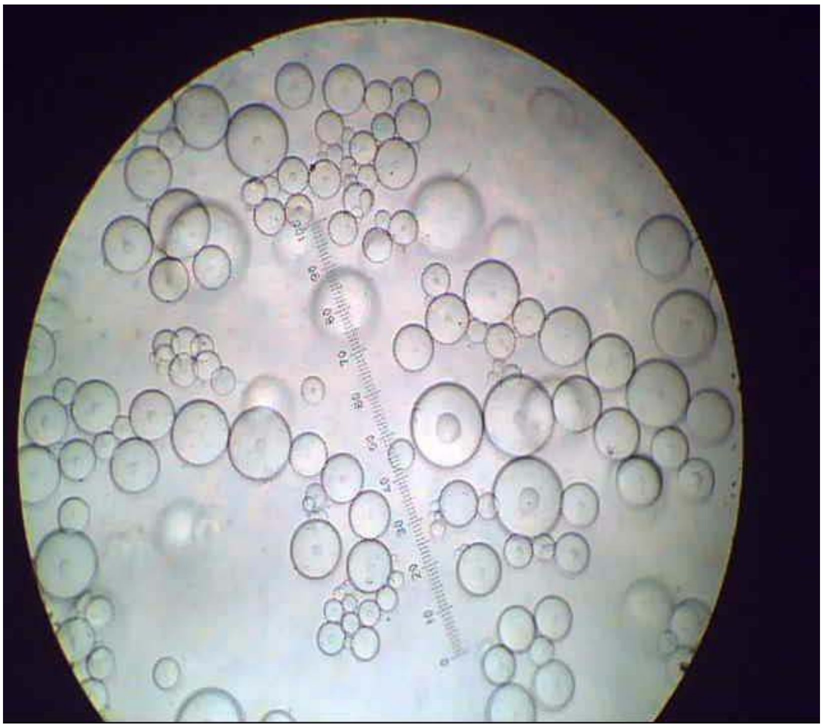

Fig. 5.3. Output Noise Free Image

The figure below shows an image in RGB Format.

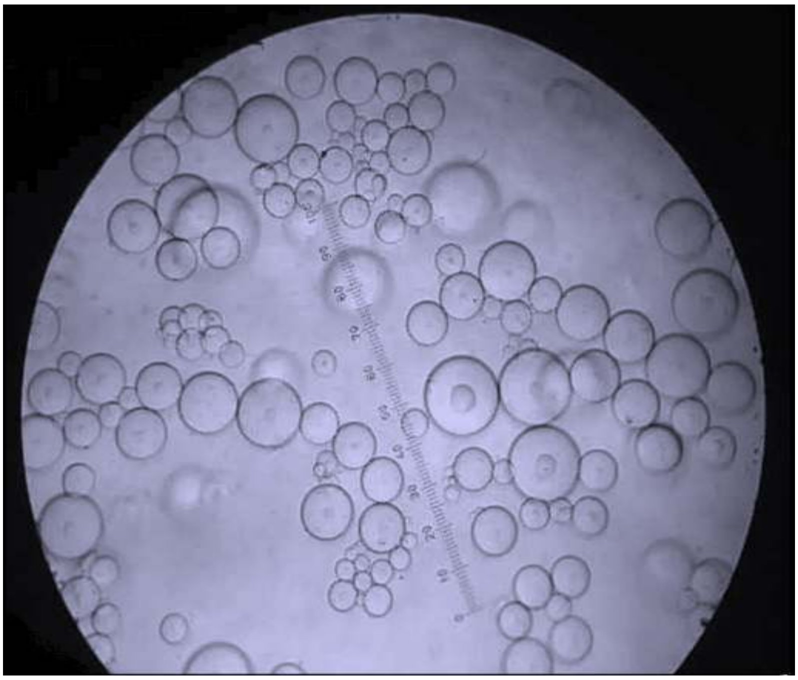

Fig. 5.4. Image in RGB Format

For 8-bit Gray Scale format, ‘0’ refers to ‘Black’ and ‘255’ refers to ‘White’.

Gray scale dumps all the color information and leaves with very little information to work with. NTSC standard is used for the conversion to gray scale

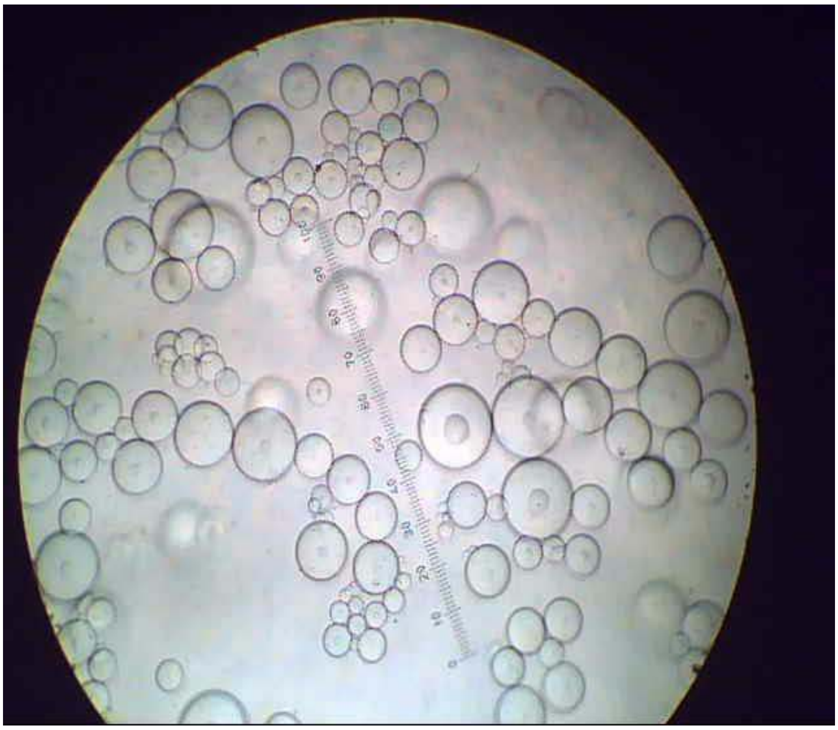

Fig. 5.5. Image in Gray Scale Format

Our next step involves Edge Detection of the Given Image. For this Gradient Edge Detection techniques have been implemented.

1) Edge Detection refers to the process of identifying and locating sharp discontinuities in an image.

2) The discontinuities are abrupt changes in pixel intensity which characterize boundaries of objects in a scene.

3) Classical methods of edge detection involve convolving the image with an operator (a 2-D filter), which is constructed to be sensitive to large gradients in the image while returning values of zero in uniform regions.

4) Before the Edge Detection process the Image is to be Binarized or converted to gray Scale. .

The following three operators are used:-

Sobel Operator : The operator consists of a pair of 3×3 convolution kernels. One kernel is simply the other rotated by 90°.

Roberts Operator **:** The operator consists of a pair of 2×2 convolution kernels.

Prewitts Operator **:** Prewitt operator is similar to the Sobel operator and is used for detecting vertical and horizontal edges in images.

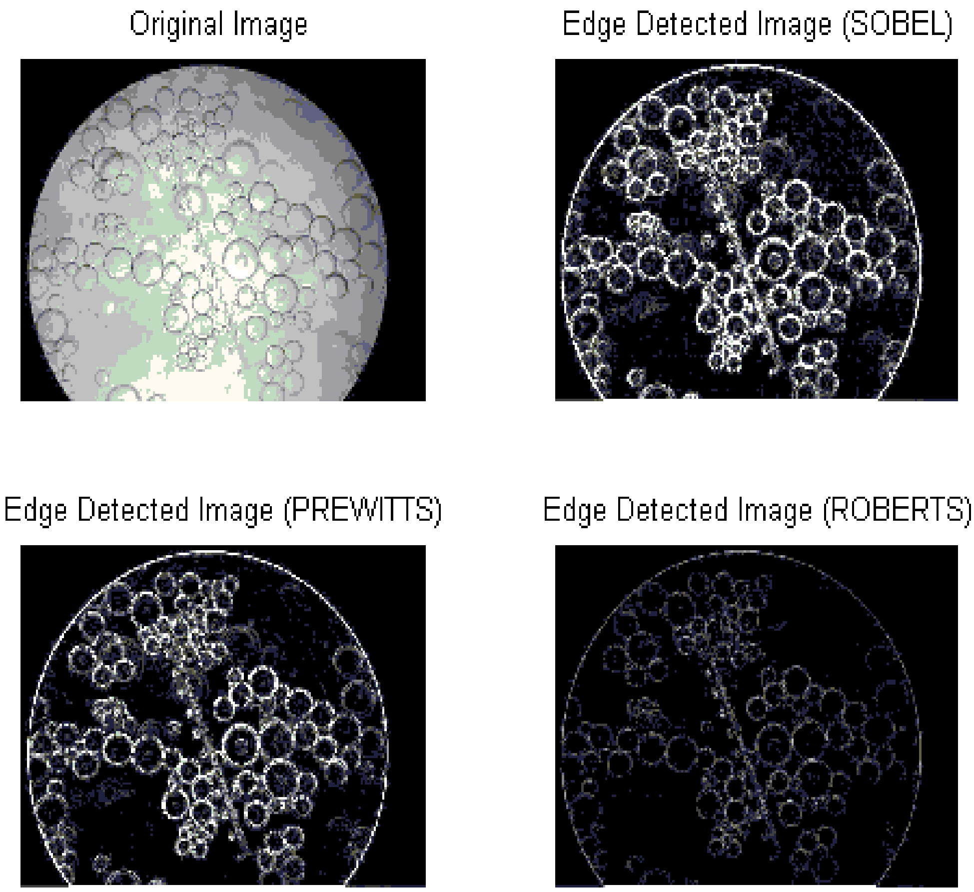

Fig. 5.6. Visual Comparison of various edge detection Algorithms

From the above figure we can conclude that SOBEL Operator gives the Best Result out of the three.

Input Images for Morphological processing

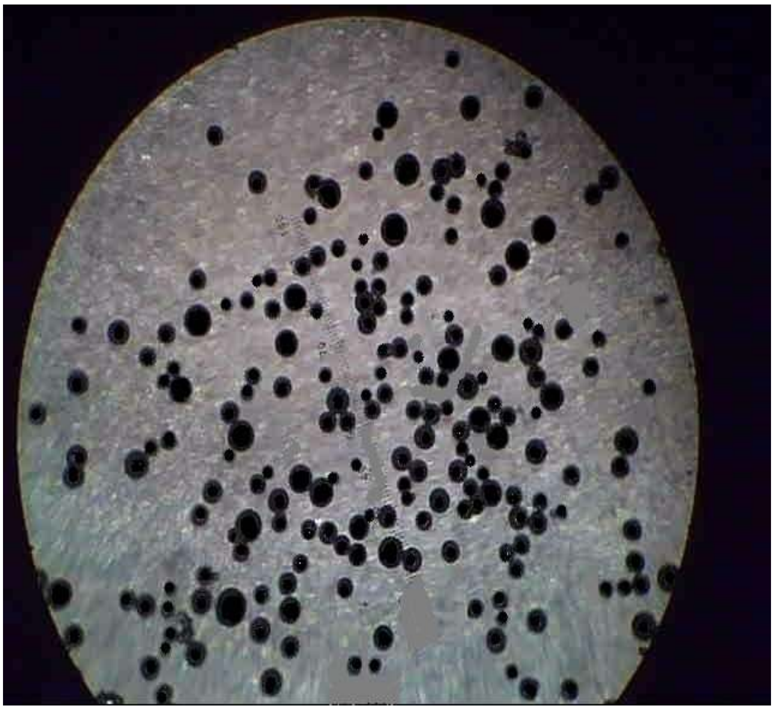

Fig. 5.7. Input Images for Morphological processing

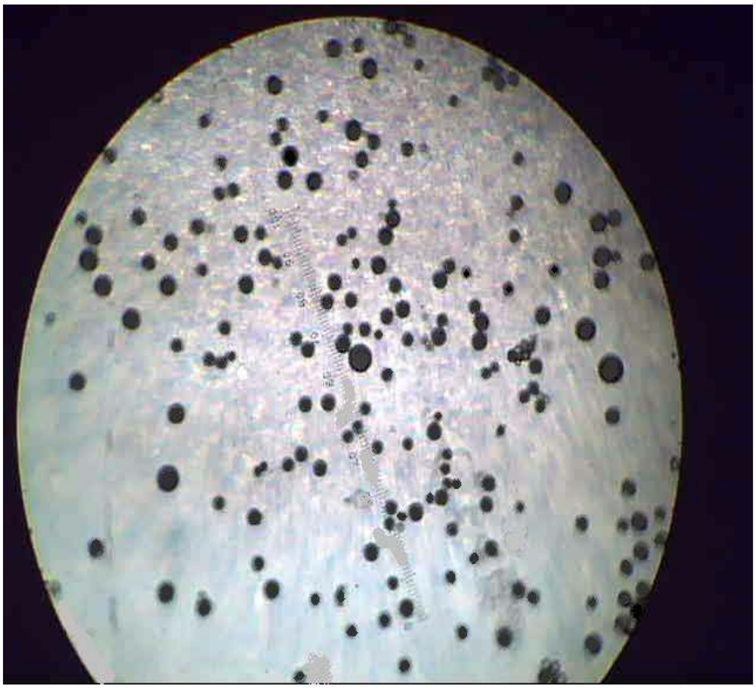

Fig. 5.8. Input Images for Morphological processing

The Images shown above represent the microscopic images of the Membrane Filter in use. The beads act as filtering pores whose job is to filter out the bacteria which exceeds its Pore size e.g. If pore size is taken as 300microns and the bacteria to be extracted out has a size of 350microns then that can be easily filtered out and the result is pure, filtered water for distillation purposes used in Medicinal applications, etc

Results from "Watershed-algorithm" application

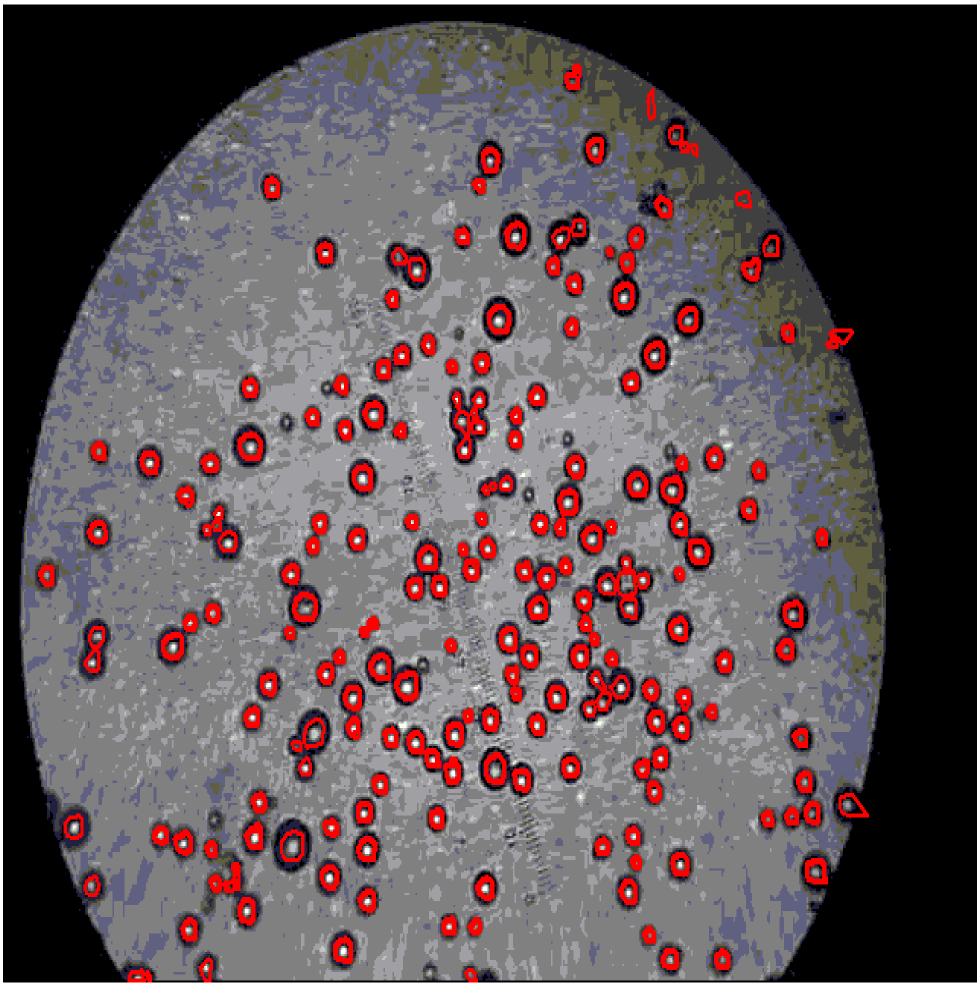

Fig. 5.9. Boundary Extracted Image

The Image shown above exhibits the results of watershed application on the Membrane Filter images. It can be easily interpreted that the boundaries of the pores are detected satisfactorily and the beads at the edge of the filter are not successfully extracted out.

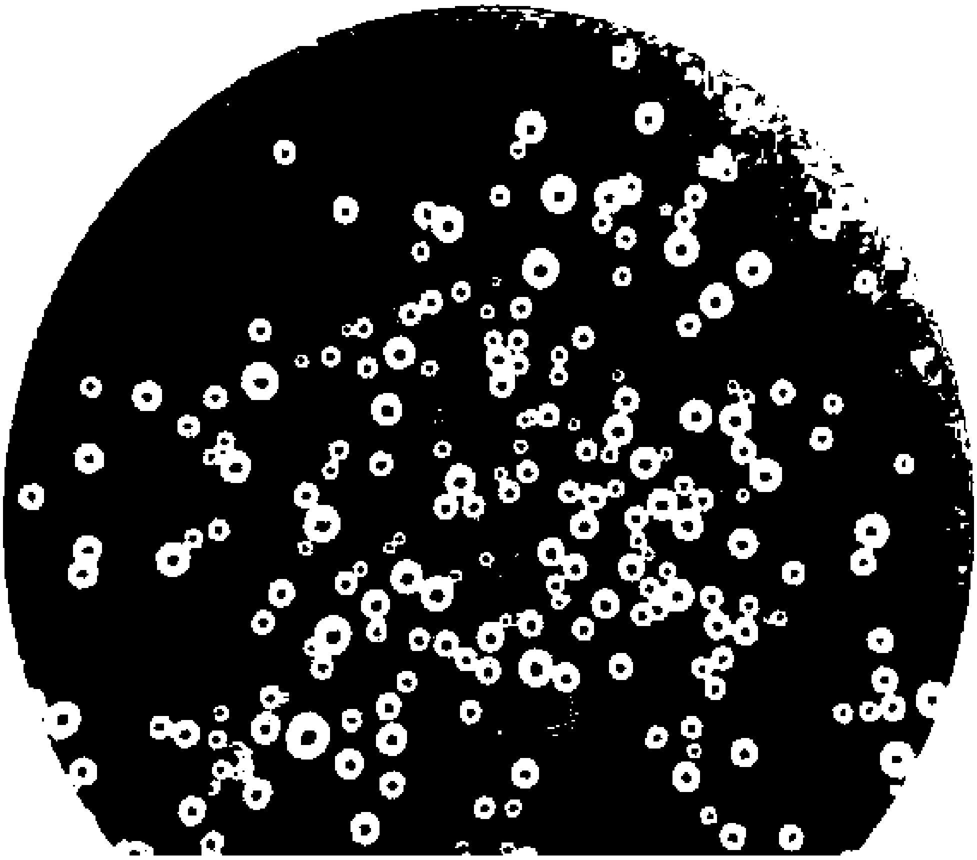

Fig. 5.10. Segmented image through Watershed Algorithm

The segmented Image from the watershed principle implementation is shown above. The main job for this segmentation purpose is to alter the colour configuration of the image to Binary one i.e. Only black and white pixels. The reason for this conversion is to make the Image processing job easier as only two colour levels are to be dealt with.

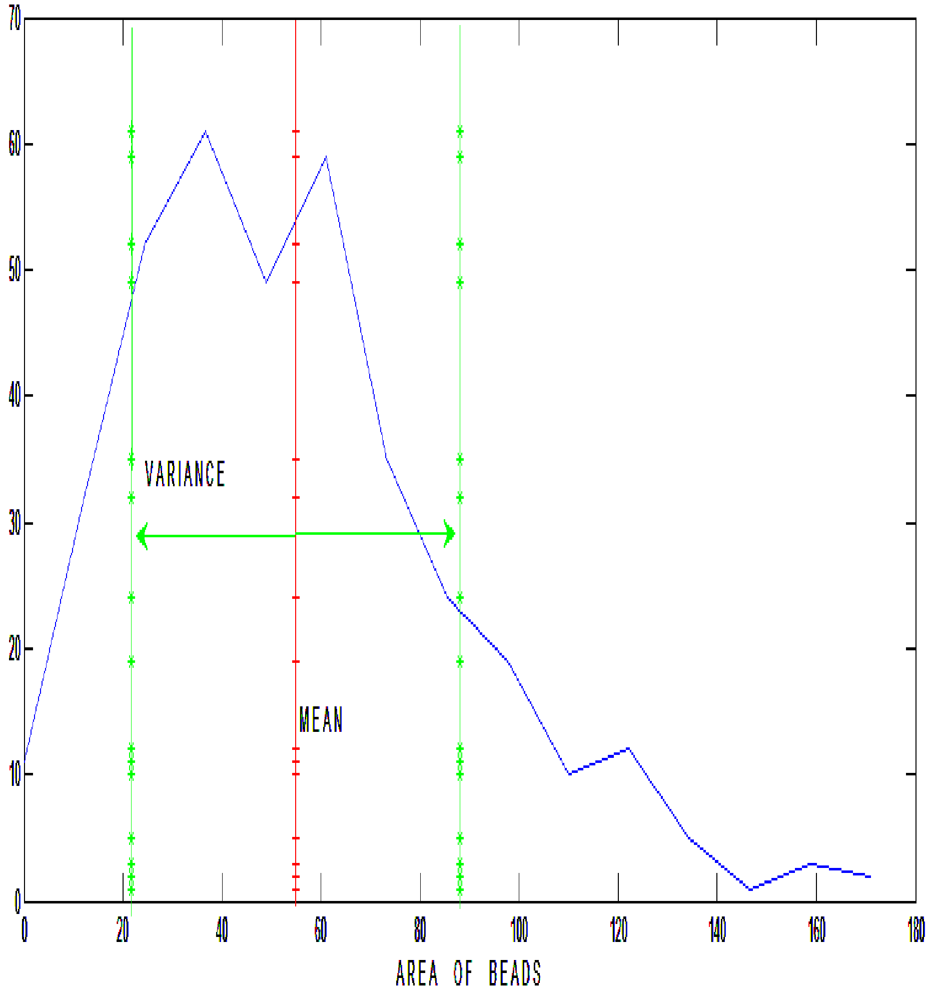

Fig. 5.11. Area distribution of Beads along with Mean and Variance

The Image above gives the graphical representation of the results from the boundary extraction of beads. The area evaluation is carried out and is subsequently plotted along with its variance and mean.

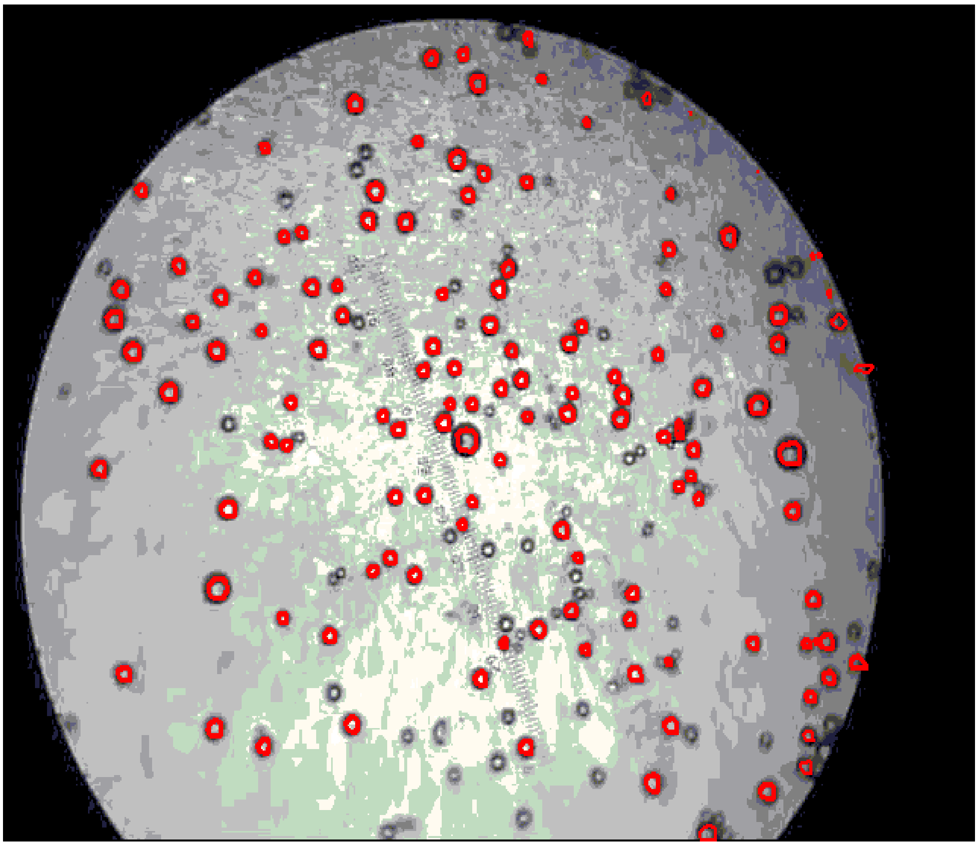

Fig. 5.12. Output image of another membrane Filter

The image in picture has relatively lesser no. of beads and the boundaries are extracted. In this image the watershed application doesn't extract the boundaries of all the beads, whereas the large beads sizes are extracted satisfactorily. The beads at the edges are not extracted and this shows the watershed principle to be vulnerable in cases the pore size is small.

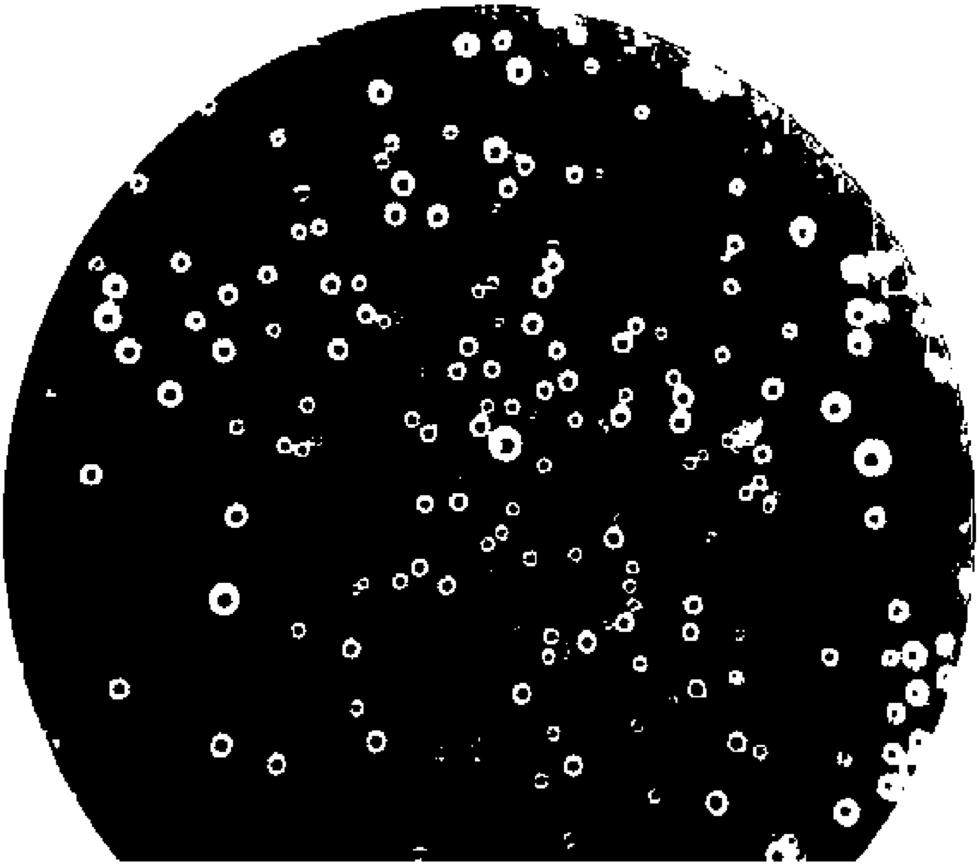

Fig. 5.13. Corresponding segmented Image

The figure above shows another segmented image, which converts the coloured input image to Binary one so as to reduce the processing complexities and henceforth better performance.

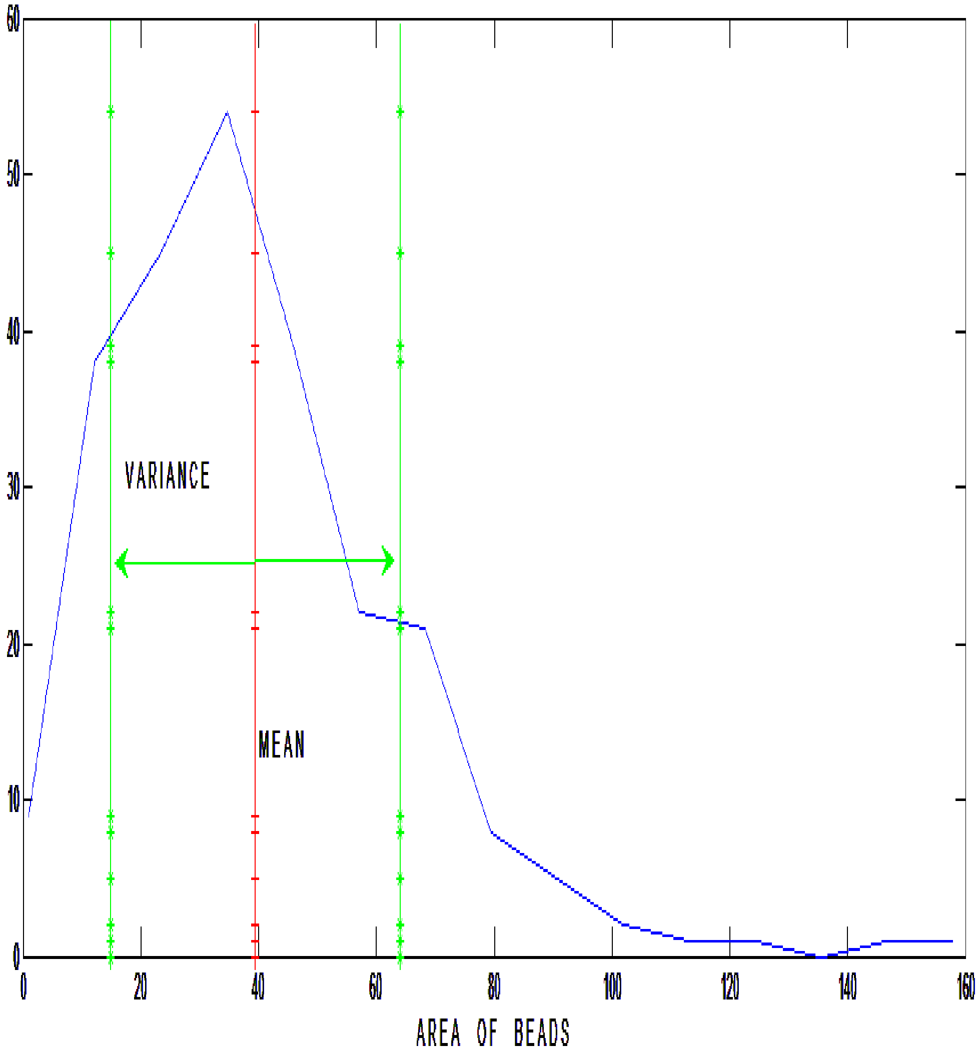

Fig. 5.14. Area distribution of Beads along with Mean and Variance

The figure above shows the area distribution of the boundary extracted beads along with corresponding variance and mean.

Results from "Active-Contour" application

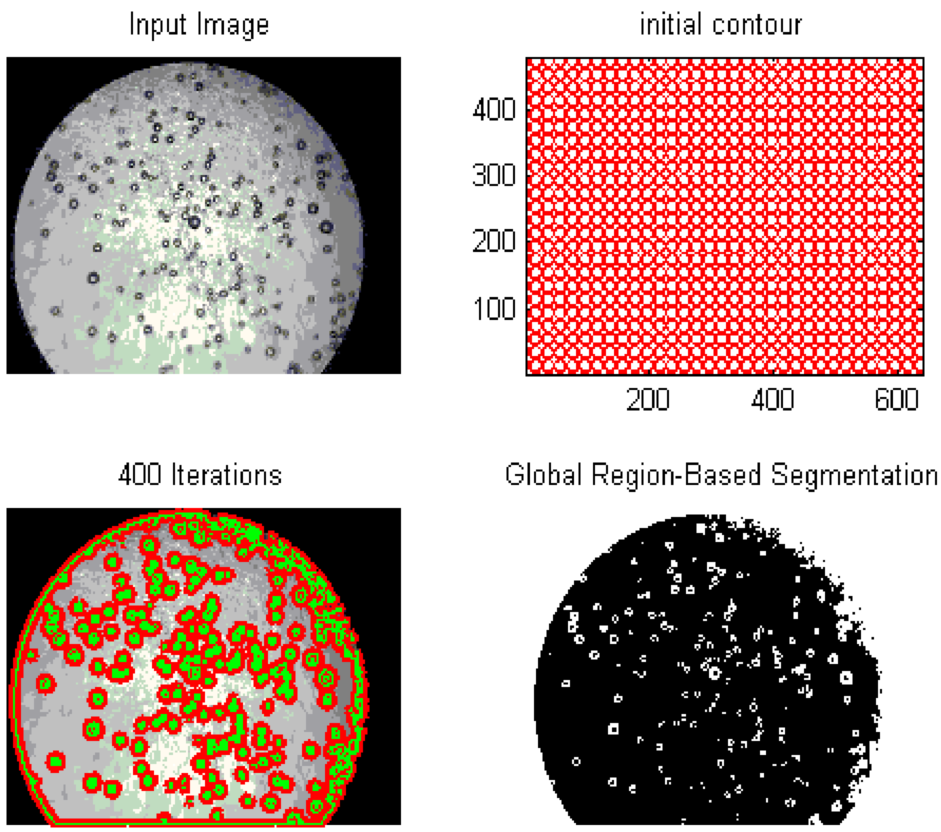

Fig. 5.15. Input image, Initial Contour, 400th iteration result and Global region based segmentation

The image above shows a subplot of the results from the application of Active Contour principle. It shows the Initial contour, the resultant image after computing 400 iterations and the Binary output segmented Image.

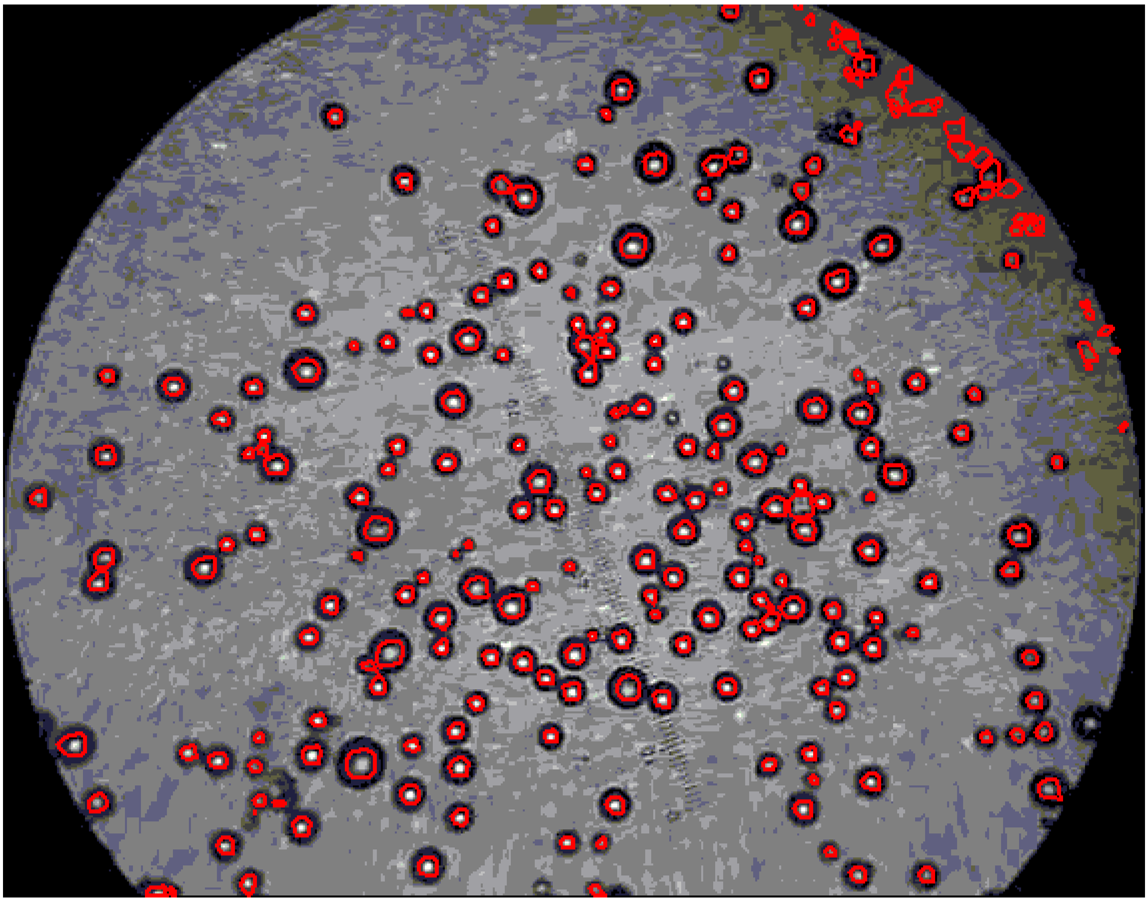

Fig. 5.16. Boundary extracted Image with Active Contouring principle

The Image above shows the boundary extracted image using Active Contouring principle.

The boundaries of beads are extracted and as can be extrapolated the results are better in comparison with the watershed application. Only a couple of beads are not detected at the edges but this method results in false detection. i.e. Detecting beads where they are not present.

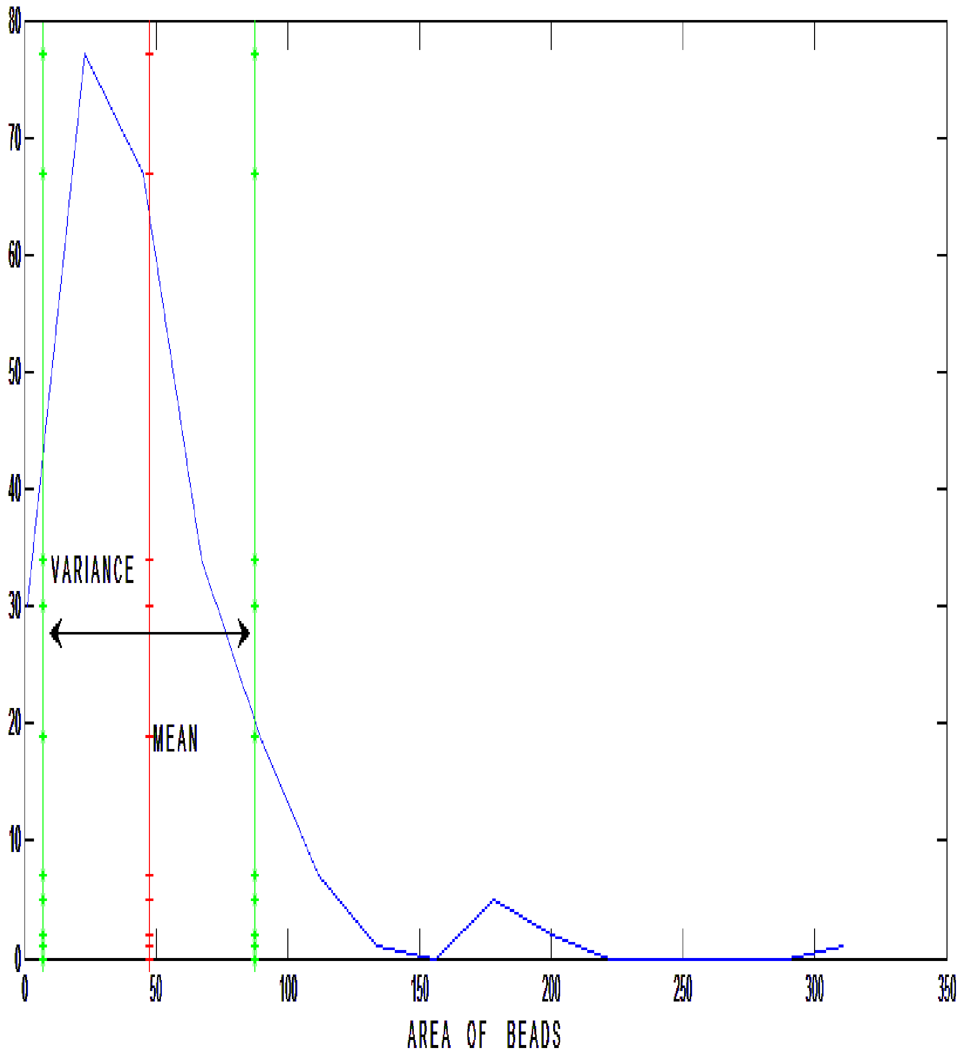

Fig. 5.17. Area distribution of Beads along with Mean and Variance

The plot above shows the area distribution of the beads extracted out after the computation and as can be deduced, the results are far better in comparison with the previous technique (watershed) as the variance is less.

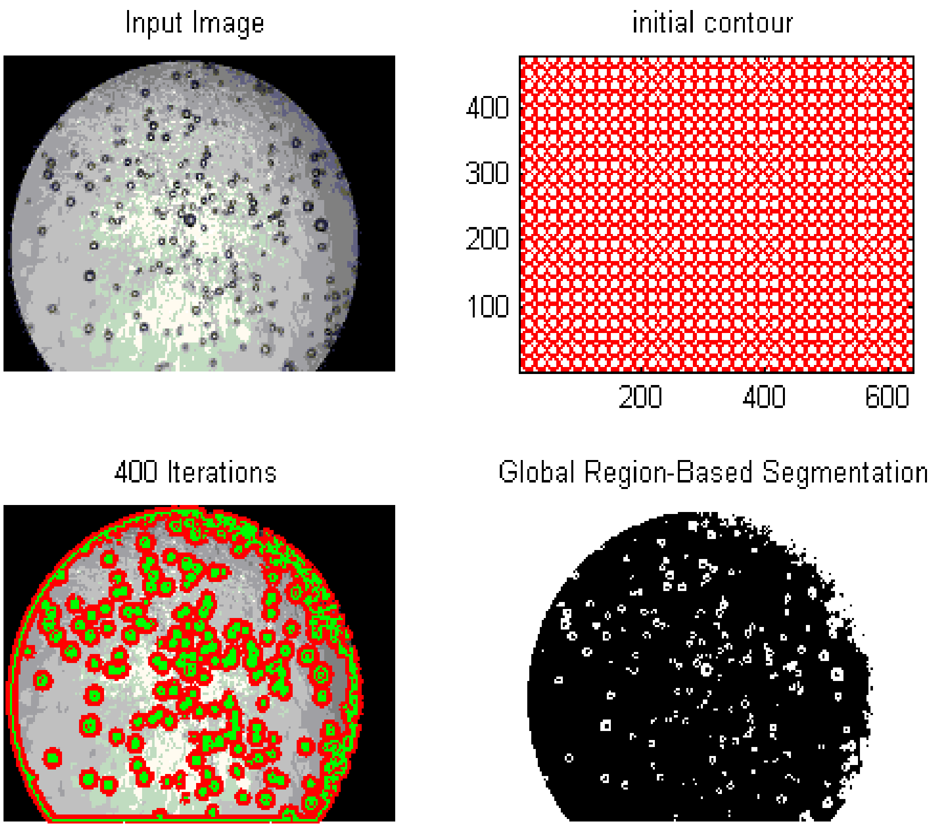

Fig. 5.18. Input image, Initial Contour, 400th iteration result and Global region based segmentation for another Membrane Filter Image

The image above shows a subplot of the results obtained from the application of Active Contour principle on another membrane filter image.

It shows the Initial contour, the resultant image after computing 400 iterations and the Binary output segmented Image.

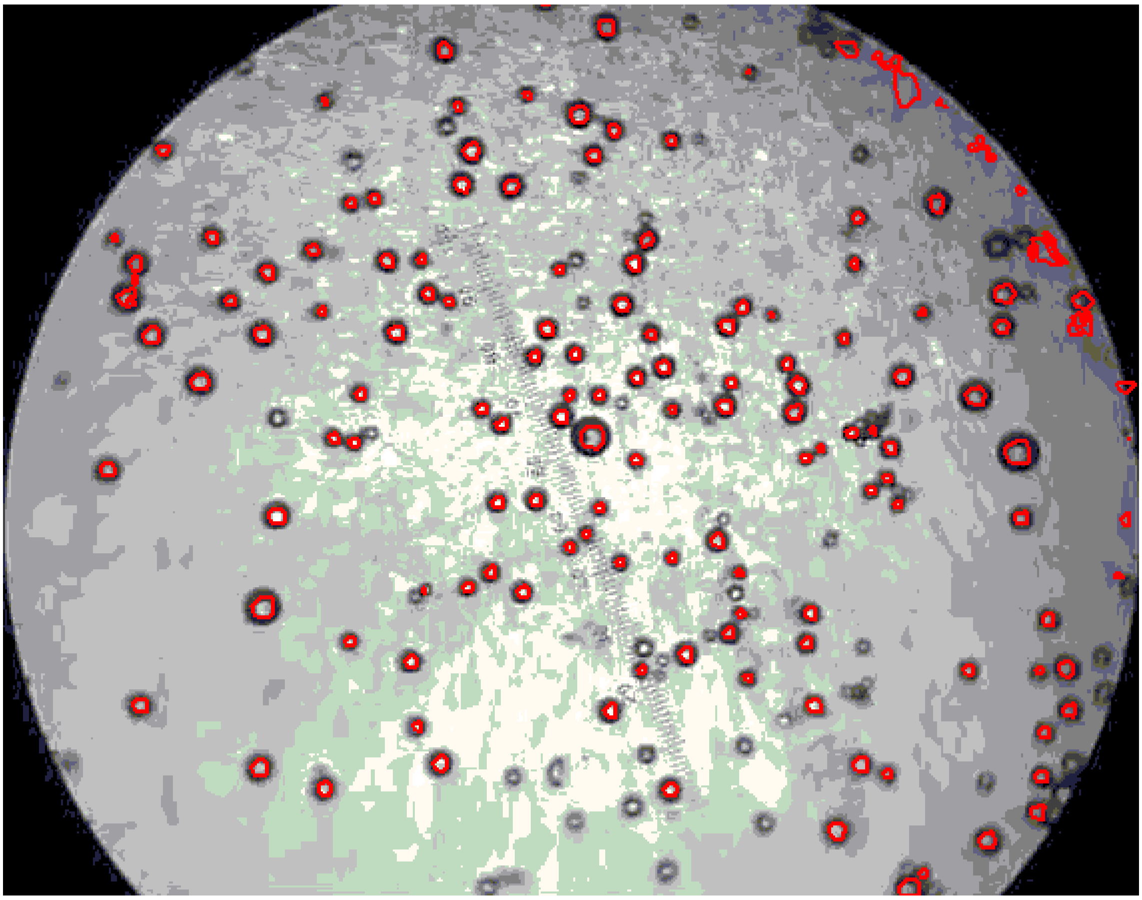

Fig. 5.19. Another Boundary extracted Image with Active Contouring principle

In the above image the boundaries of beads are extracted and some beads are not detected at all. This presents a limitation to this technique as the beads at the edges are not detected at all.

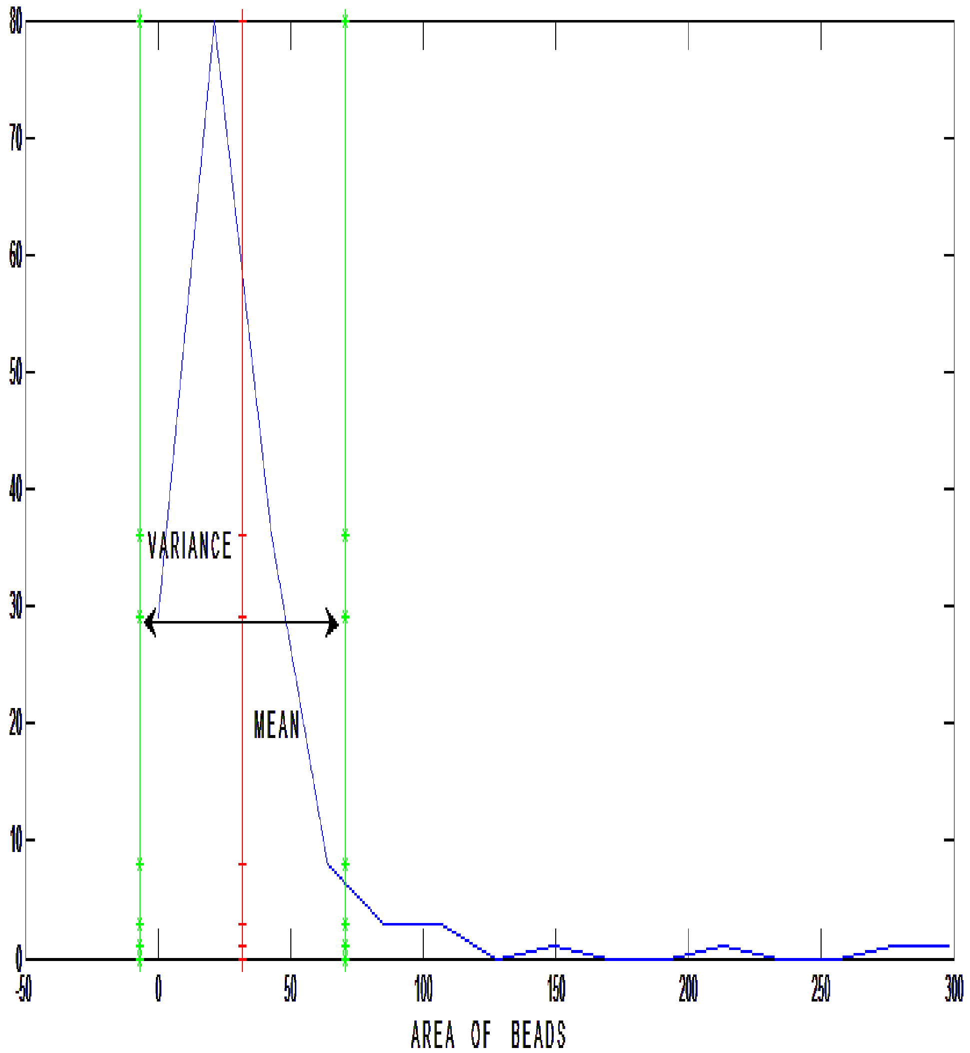

Fig. 5.20. Area distribution of Beads along with Mean and Variance

The plot above shows the area of the beads along with the corresponding mean and variance.

As can be deduced from this image the bulk concentration is at the lower end i.e. The beads are small.

Results from application of "Circular Hough Transform" Technique

Output Image :

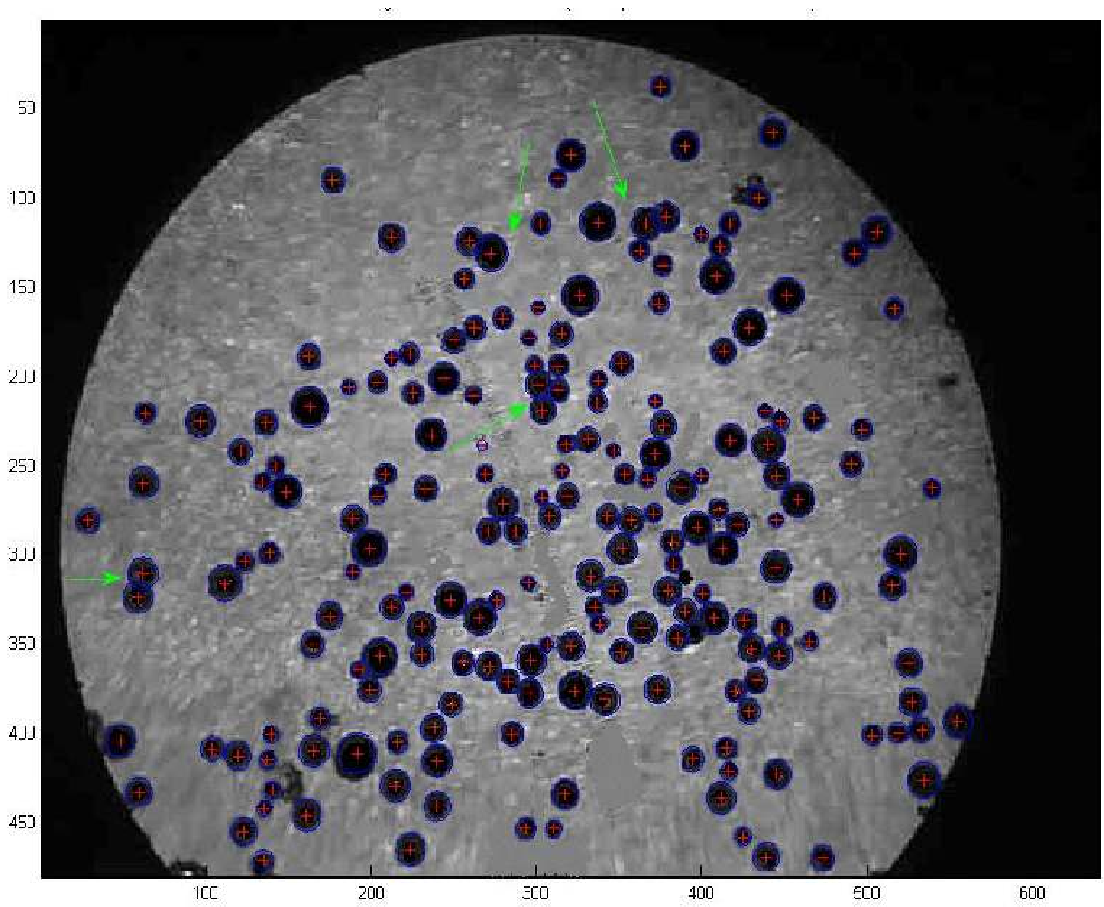

Fig. 5.21. Boundary Extracted Image along with "Arrow-Marked" Overlapping Separation of beads

The image above shows the precisely accurate boundary extractions of the beads. The boundary extraction part is performed by the other morphological operations as well(like watershed, active contouring, etc) but in case where the beads overlap the extraction process becomes complex and the techniques fail.

The overlapped beads are arrow marked and as can be seen the boundaries are extracted flawlessly.

Not only the overlapped beads but the relatively easier spread up single beads are detected and their boundaries are extracted easily.

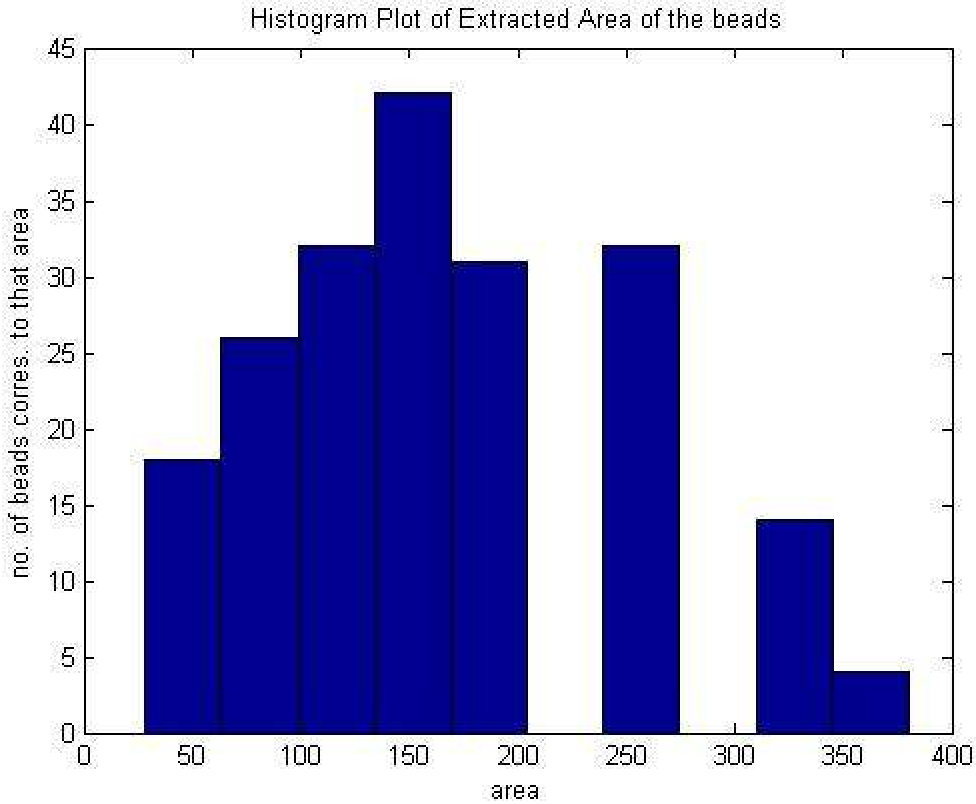

Fig. 5.22. Corresponding Histogram Plot

The histogram plot above shows the area distribution along with no. of beads corresponding to that particular area.

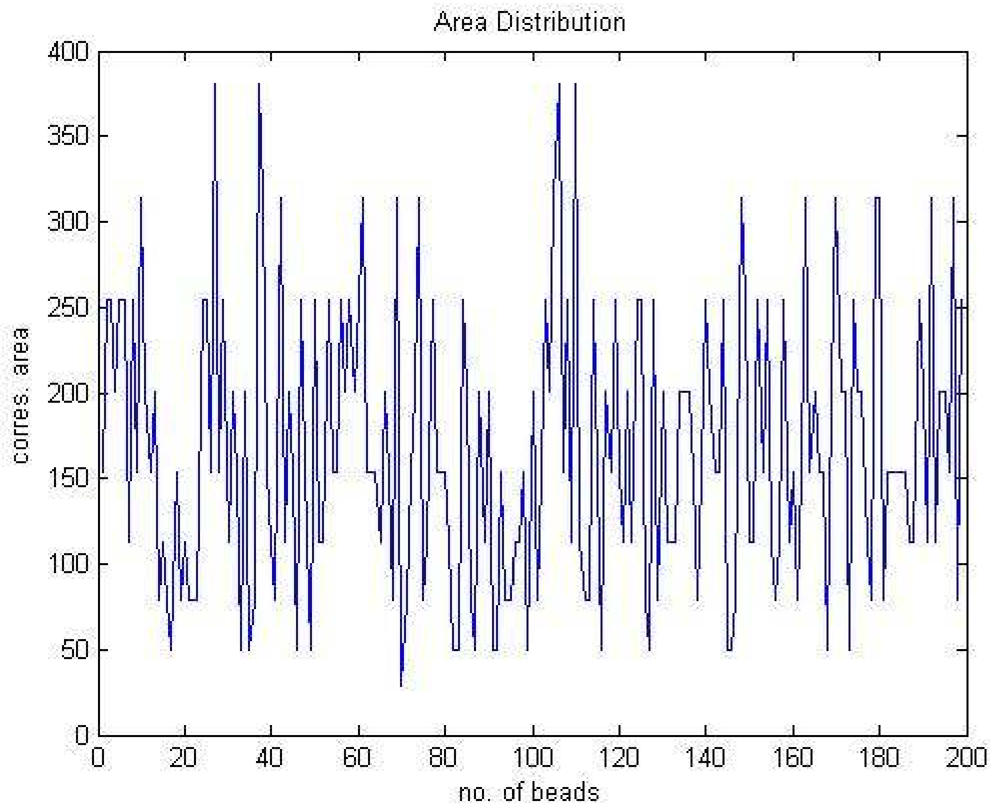

Fig. 5.23. Distribution curve shown below

The area distribution curve gives an idea about the no. of beads corresponding to that particular area.

So, with this curve it can be inferred that the max area of beads comes out to be around 375 and the beads corresponding to that area are also shown above.

Another Output Image :

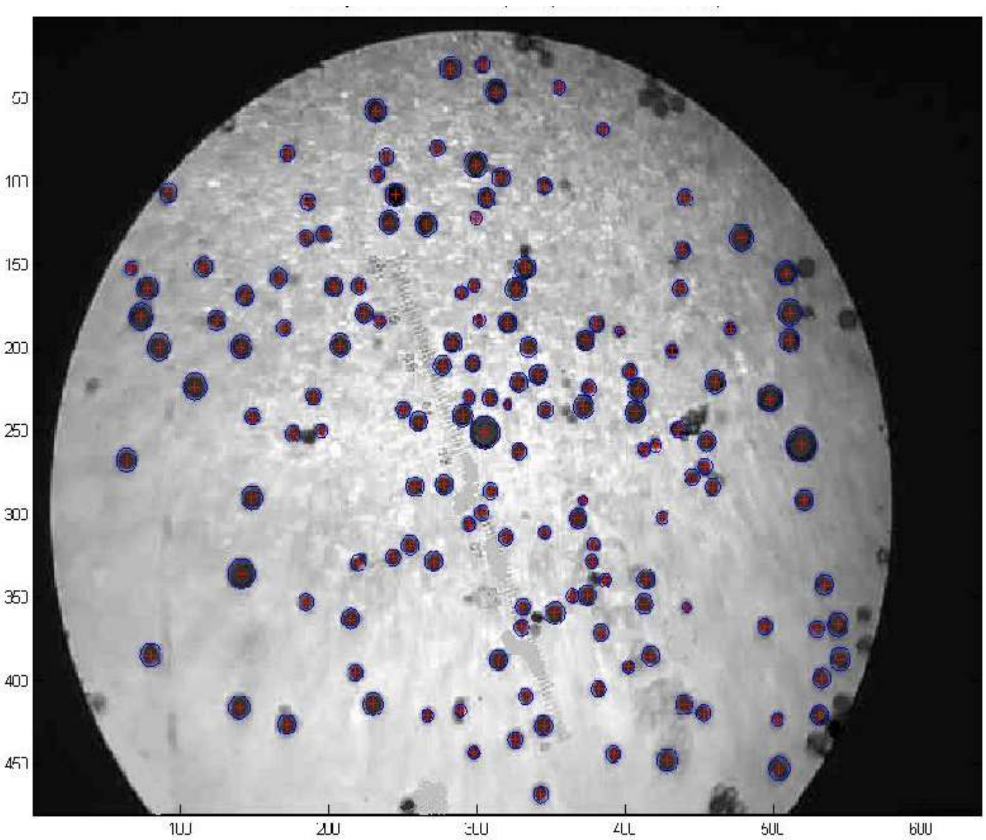

Fig. 5.24. Boundary Extracted Image

The image above shows the boundary extractions, this also results in false detections. In order to counter the false detections the pores are compromised i.e. The beads near the top right part of the image are not detected.

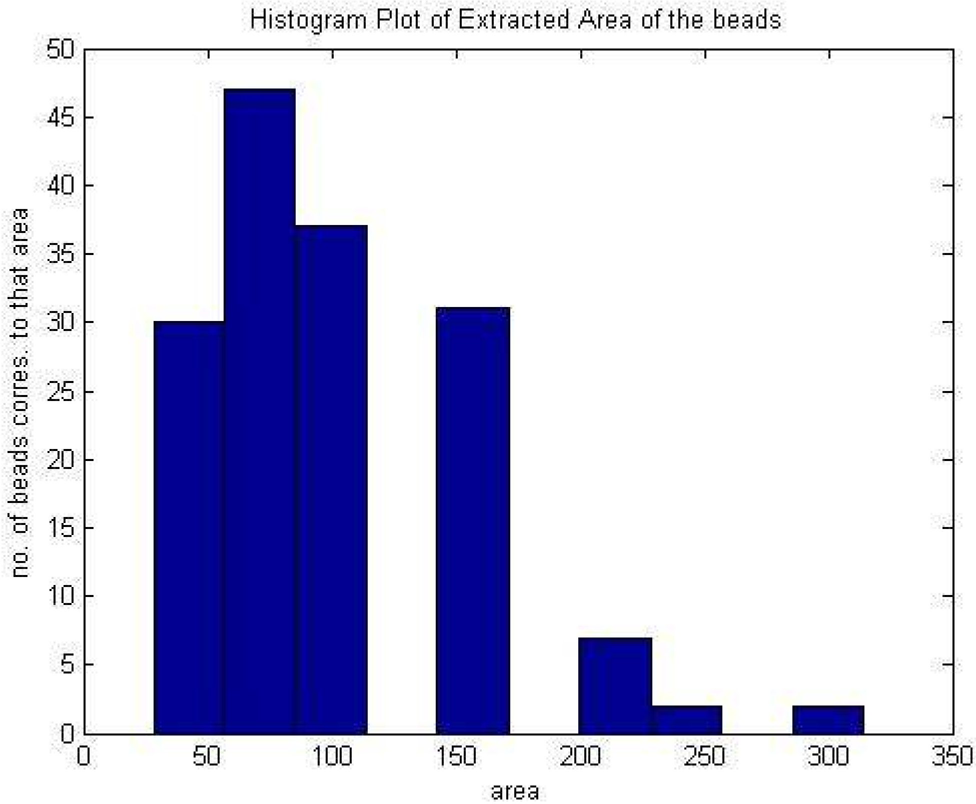

Fig. 5.25. Corresponding Histogram Plot

The image above shows the histogram plot of the detected beads.

As can be inferred from this plot, the bulk concentration is towards the left side of the plot, indicating that the beads are having less area i.e. The beads are smaller compared to the former image.

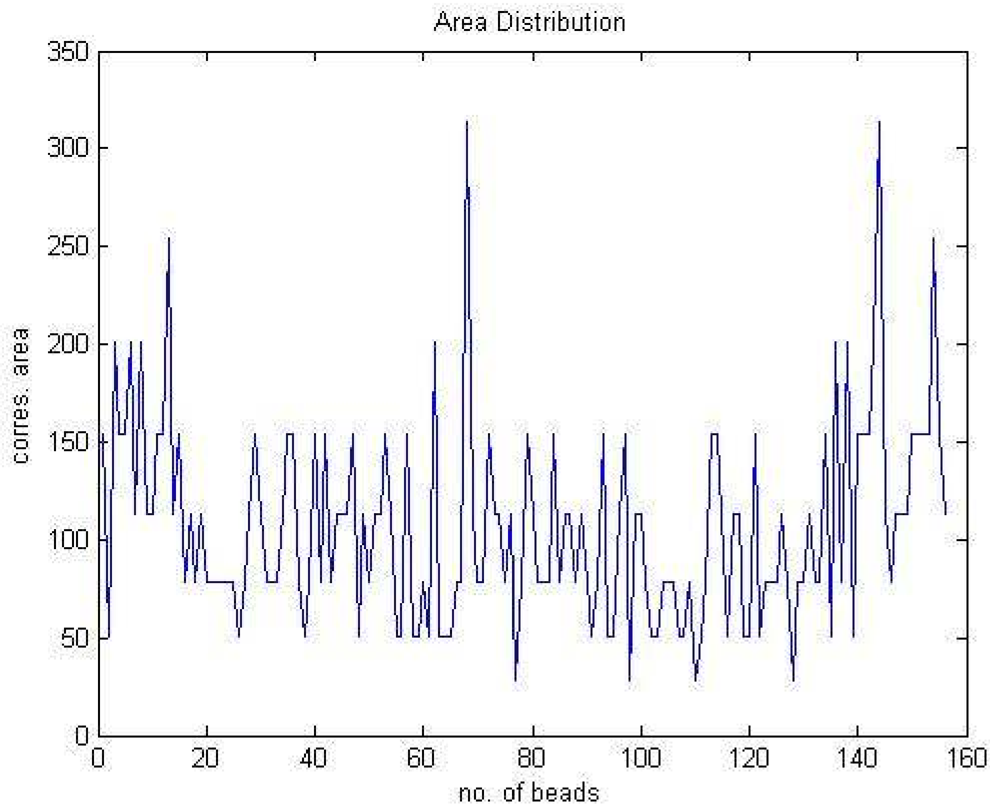

Fig. 5.26. Distribution curve shown below

The above distribution curve indicates the bead size is small and the max. area comes out to be around 305.

Also inferred is less no. of beads compared to the former image.

CONCLUSION

The Main aim of this dissertation is to produce statistical analysis of a membrane filter for Quality check purposes. It is carried through implementation and analysis of various feature extraction techniques.

The results from the Image processing techniques are compared and analyzed based upon the boundary extraction results.

As seen in the simulation results the results from the Active Contouring method outclass those form the Watershed method, but both these do not somehow provide the desired results as in case of overlapping beads, both the techniques fail.

Whereas, with the Circular Hough transform not only the problem of complex overlapping beads is solved but the results are far better in each and every aspect.

Finally, the area of the extracted beads is determined.So, the dissertation aim of producing a Statistical Quality check analysis of a membrane filter is achieved and a Semi- Automatic system is presented through this work.

Future Work includes utilization of the technique for images with low lighting conditions e.g. Images with low light intensity. Limitations arise for such images as the image processing techniques include binary segmentation which is an integral part of any image synthesis analysis and needs careful application.

According to the quality of the membrane filter obtained it can be used for various applications within the industry, science and research. Some of applications are water recovery and recycle, fluid and water purification, capture and recovery of fluid suspended products (biological, minerals etc.), desalination of water, medical and pharmaceutical use, bacteriological examination in air and water and food and dairy industry.

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