



An Innovative Approach on Concrete Beam Renovation Based on Threshold Image Segmentation by Multivariate Analysis

D Neguja and A Senthirajan

EasyChair preprints are intended for rapid dissemination of research results and are integrated with the rest of EasyChair.

October 20, 2021

An Innovative Approach on concrete beam renovation based on threshold image segmentation by multivariate analysis

D.Neguja
Department of Computer science
St.Joseph's College of arts and science
Vaikalipatti,Tamilnadu, INDIA
neguja@gmail.com

Dr.A.Senthilrajan
Department of Computational logistics
Alagappa University
Karaikudi,Tamilnadu, India
agni_senthil@yahoo.com

Abstract - The building renovation process is the most time-consuming aspect. This paper grants the possibility of applying the multiple variable detections from segmentation of image components by a multivariate - technique using Convolutional function to assist automated reconstruction for the renovation of beam concrete. The research has two parts: the first one is multivariable dataset multivariate, with image segmentation using multiple threshold values are made for the proposed research, and the second is testing the data sets of segments, by using Convolutional functions applied for more images to make predictions. In the manual inspection, the sketch of the beam is prepared manually, and the conditions of the irregularities in the image are noted. Since the manual approach completely depends on the specialist's knowledge, manpower, and work pressure, it lacks objectivity in the quantitative analysis. So, automatic image segmentation with multi-thresholding based on Convolutional function is proposed as a renovating element to obtain a tool for the reconstruction of the image.

Index Terms -image, threshold, multivariate, Convolutional, renovation

I. INTRODUCTION

Multi-level threshold segmentation has an important research value in image segmentation, which can effectively solve the problem of segmentation of complex images, but the computational complexity increases accordingly [1]. Several methods have been used to solve threshold selection problems; the method is based on the mixture of Convolutional functions to approximate the 1D histogram of a gray level image and whose parameters are calculated using the Convolutional function. Each Convolutional function approximates the image segment, representing a pixel class and therefore a threshold point is used [2]. Traditional gradient descent and other deterministic and exact methods are used to solve these complicated types of problems. Image segmentation based on multi-threshold image segmentation (MTIS) method with a non-local means 2D image segments with an entropy-based method. In this, it was compared with low and high threshold levels [3]. Fusing several good algorithms using a hierarchical majority yielded segmentations that consistently used for multi-level thresholding, indicating threshold values for further methodological improvements [4]. The different threshold values are applied to these images. The performances are measured based on threshold segment values [5]. An OTSU threshold technique for image segmentation, which gives the approximate result as compared with the other methods and simple. Segmentation subdivides the image into different parts.[6]. Each pixel in an image has its threshold, which is estimated by calculating the statistical information of

its neighbourhood pixels.[7]. Otsu's method performs nonparametric image threshold [8]. Image segmentation analysis at low threshold levels and high threshold levels are also respectively carried out [9]. Apply various threshold techniques on different images and find the best suitable technique for generating binary images [10]. Mechanically detecting buildings from satellite images has a lot of potential applications, from monitoring the images in remote areas to evaluate the available surface to multiple segments [11]. The threshold values of each particle are initialized in the range $[g_{min}, g_{max}]$. The thresholds are sorted in the method optionally [12]. Cracks in concrete structures not only affect the appearance of the structure, but also accelerate the aging of the structure, and reduce the bearing capacity and safety of the structure [13]. The segmentation is more uniform, with accurate and smoother boundaries, besides being not so susceptible to divide [14]. In the process of partitioning the unwanted images based on the separation of pixel result, the surface of beam concrete with multiple segments can be extracted, modeled, manipulated measured, and visualized[15].

II. METHODOLOGY

2.1 Innovative Process of remodel

A flow chart is shown to illustrate the activities covered in this research. The following are the step-by-step procedures used in the design of the concrete is rescheduled as shown in Figure 2.1.

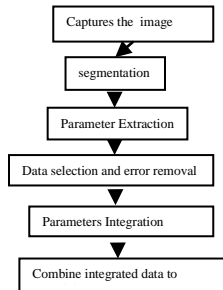


Figure 2.1. Flowchart for the innovative process.

Figure 2.2 gives the innovative segmentation process which explains the collection of beam images and how the images are segmented to multivariate threshold values. Then the strong resolute segments are collected and integrated to form the remodel beam structure.

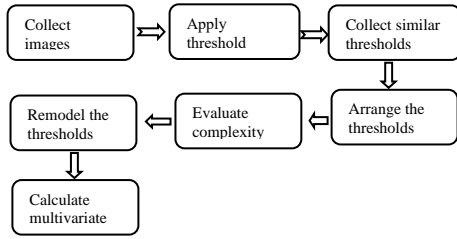


Figure 2.2. The innovated segmentation process.

The proposed innovative process of beam concrete is characterized by elements with specific tasks by allowing for the execution of a proper capacity design. The design procedure is force-based and is applied by considering the latticed statically determined scheme representing the limit behavior of the beam.

The design procedure is articulated according to the following 9 steps:

1. Definition of the static equivalent lateral loads and calculation of the segments.
2. Design of the segmented sections of the multiple elements in the renovation.
3. Capacity design of the combination of the threshold segments and the adjacent elements performed with the renovation procedure.
4. Calculation of geometric over-strength factors of image;
5. Calculation of axial loads in non-structured image beam elements by combining the effects of gravity loads of segments
6. Capacity design of the newly innovated image segments of reinforced concrete by concrete crushing
7. Design of the selected segments of images in grip.
8. Check the compressed thresholded segments and design of new innovated segments of the image.
9. Calculation of the length of the dissipative element, to ensure the compliance between local and global thresholding.

2.2 Convolutional approximation

The Convolutional method for segmentation. The image is inputted and the best fitting parameters are obtained. The Convolutional approximation is applied to evaluate multiple variables for thresholding. Then segmentation process is applied for the image and extracted for filtering process.

Finally the rescheduled image is evaluated for restructure. Let consider an image holding L gray levels $[0, \dots, L-1]$ whose distribution is displayed within a histogram $h(g)$. To simplify the description, the histogram is normalized just as a probability distribution function, yielding:

$$h(g) = \frac{ng}{N}, h(g) > 0$$

$$\sum_{g=0}^{L-1} ng = N, \text{ and } \sum_{g=0}^{L-1} h(g) = 1 \quad \dots \text{Eqn. 1}$$

where ng denotes the number of pixels with gray level g and N is the total number of pixels in the image. The histogram function can thus be contained into a mix of Convolutional probability functions of the form:

$$P(x) = \sum_{i=1}^K P_i - p_i(x) = \sum_{i=1}^K \left[\frac{P_i}{\sqrt{2\pi}\sigma_i} \exp \left(-\frac{(x-\mu_i)^2}{2\sigma_i^2} \right) \right] \dots \text{Eqn. 2.}$$

Where P_i being the probability of class i . $p_i(x)$ is being the probability distribution of gray level random variable x in class i with μ_i and σ_i being the mean and standard deviation of the i th probability distribution function and K be the number of classes within the image. In addition the

constraint $\sum_{i=1}^k Z_i = 1$ must be satisfied. The mean square error

The mean square error is used to estimate 3000 parameters Z_i , μ_i and σ_i , where $i = 1, \dots, k$. For instance, the mean square error between the convolutional formula $p(x_i)$ and the experimental histogram function $h(x_i)$ is now defined as follows :

$$J = \frac{1}{n} \sum_{j=1}^n \left[p(x_j) - h(x_j) \right]^2 + \omega \left[\sum_{i=1}^k P_i - 1 \right] \dots \text{Eqn. 3}$$

Assuming an n -point histogram and ω being the penalty associated with the constraint

$$\sum_{i=1}^k P_i = 1.$$

In general, the estimation of the parameters that minimize the square error produced by the Convolutional mixture is not a simple problem. A straightforward method is to consider the partial derivatives of the error function to zero, obtaining a set of simultaneous transcendental equations. However, an analytical solution is not available considering the non-linear nature of the equations. Unfortunately, such methods may also get easily stuck within local minima. The Convolutional curve for x , with variance σ is created.

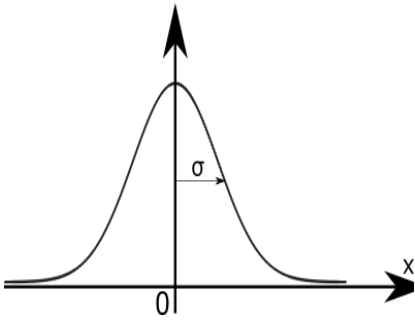


Figure 2.3 Convolutional curve

Segmented multivariate, also known as piecewise multivariate or broken-stick multivariate, is a method in multivariate analysis in which the independent variable is partitioned into intervals and a separate line segment is fit to each interval. Segmented multivariate analysis can also be performed on multivariate data by partitioning the various independent variables. Segmented multivariate is useful when the independent variables, clustered into different groups, exhibit different relationships between the variables in these regions. The boundaries between the segments are breakpoints. Segmented linear multivariate is segmented multivariate whereby the relations in the intervals are obtained by linear multivariate. Segmented multivariate analysis is based on the presence of a set of (y , x) data, in which y is the dependent variable and x the independent variable.

The least-squares method applied separately to each segment, by which the two multivariate lines are made to fit the data set as closely as possible while minimizing the sum of squares of the differences between observed (y) and calculated (Yr) values of the dependent variable, results in the following two equations:

$$Y_r = A_1 \cdot x + K_1 \quad \text{for } x < \text{BP (breakpoint)} \quad \text{---- Eqn.4.1}$$

$$Y_r = A_2 \cdot x + K_2 \quad \text{for } x > \text{BP (breakpoint)} \quad \text{---- Eqn. 4.2}$$

where:

Yr is the expected (predicted) value of y for a certain value of x;

A1 and A2 are multivariate coefficients (indicating the slope of the line segments);

K1 and K2 are multivariate constants (indicating the intercept at the y-axis).

The data may show many types or trends as in figures, .

The method also yields two correlation coefficients (R):

$$R_{12} = \frac{\sum(y - Y_r)^2}{\sum(y - Y_{a1})^2} \quad \text{for } x < \text{BP (breakpoint)} \quad \text{---- Eqn.4.}$$

$$R_{22} = \frac{\sum(y - Y_r)^2}{\sum(y - Y_{a2})^2} \quad \text{for } x > \text{BP (breakpoint)} \quad \text{---- Eqn. 5.}$$

Where $\sum(y - Y_r)^2$ $\{\displaystyle \sum (y - Y_{\{r\}})^{\{2\}}\}$ is the minimized SSD per segment and Ya1 and Ya2 are the average values of y in the respective segments.

Segmented linear multivariate with two segments separated by a multivariate point can be useful to quantify an abrupt change of the response function (Yr) of a varying influential factor

(x). The multivariate point can be interpreted as a critical, safe, or threshold value beyond or below which (un)desired effects occur. The multivariate point can be important in decision-making.

Figure 2.4 shows the linear multivariate process on segmentation. The amplitude of threshold is computed from gray scale of histogram image by computing linear multivariate with 3D convolution. Then adaptive parameters are calculated by geometrization point values. By using point values form the region of reconstruction then apply the algorithm of restructuring to the parameters.

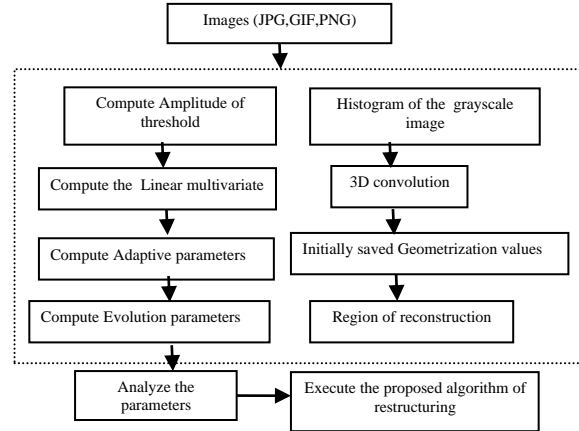


Figure 2.4. Flow chart for Linear multivariate on segmentation

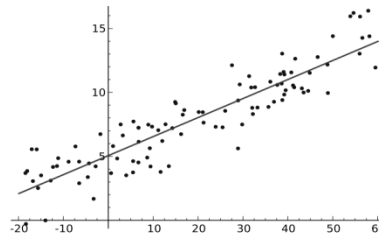


Figure 2.5. Segmented multivariate analysis

Figure 2.5. Illustrates some of the segmented results and multivariate types obtainable.

Segmented multivariate analysis is based on the presence of a set of (y , x) data, in which y is the dependent variable and x the independent variable. The least-squares method applied separately to each segment, by which the two multivariate lines are made to fit the data set as closely as possible while minimizing the sum of squares of the differences (SSD) between observed (y) and calculated (Yr) values of the dependent variable, results in the following two equations:

$$Y_r = A_1 \cdot x + K_1 \quad \text{for } x < \text{RP (multivariate point)}$$

$$Y_r = A_2 \cdot x + K_2 \quad \text{for } x > \text{RP (multivariate point)}$$

where: Yr is the expected (predicted) value of y for a certain value of x;

A1 and A2 are multivariate coefficients (indicating the slope of the line segments);
 K1 and K2 are multivariate constants (indicating the intercept at the y-axis).

The data may show many types of trends, .

The method also yields two correlation coefficients (R):

$$R_1^2 = \frac{\sum (y - Y_r)^2}{\sum (y - Y_{a1})^2}$$

for $x < RP$

$$R_2^2 = \frac{\sum (y - Y_{\sigma 1})^2}{\sum (y - Y_r)^2}$$

where RP is the multivariate point.
 and

$$R_1^2 = \frac{\sum (y - Y_{a1})^2}{\sum (y - Y_r)^2}$$

$$R_2^2 = \frac{\sum (y - Y_{a2})^2}{\sum (y - Y_r)^2}$$

for $x > RP$

where: $\sum (y - Y_r)^2$
 $\sum (y - Y_{a1})^2$
 $\sum (y - Y_{a2})^2$
 is the minimized SSD per segment and Ya1 and Ya2 are the average values of y in the respective segments. In the determination of the most suitable parameters, statistical tests must be performed to ensure which parameter is reliable (significant). When no significant multivariate point can be detected, one must fall back on a multivariate without a multivariate point.

Significance of the breakpoint (BP) by expressing BP as a function of multivariate coefficients A1 and A2 and the means Y1 and Y2 of the y-data and the means X1 and X2 of the x data (left and right of BP), using the laws of propagation of errors in additions and multiplications to compute the standard error (SE) of BP, and applying Student's t-test Significance of A1 and A2 applying Student's t-distribution and the standard error SE of A1 and A2

Significance of the difference of A1 and A2 applying Student's t-distribution using the SE of their difference.

Significance of the difference of Y1 and Y2 applying Student's t-distribution using the SE of their difference.

A more formal statistical approach to test for the existence of a breakpoint is via the pseudo score test which does not require estimation of the segmented line.

2.3 Threshold segmenting multivariate values

Threshold segmentation can be understood as an optimization problem in a space made up of grey levels. That is, to find the levels to class the pixels by which some objective functions achieve the optimum. A typical classification of threshold segmentation is based on the objective function, such as minimum error, maximum interclass variance, maximum entropy, etc. Generally, Otsu's method, Kapur's method, Otsu's method and Kapur's method are, respectively, the most typical examples of the methods based on variance and entropy. Based on the objective

functions of the two methods, we achieve multilevel thresholding with the proposed algorithm. K thresholds are used in image segmentation could correspond to an optimization problem in k dimension space: $n [0, L-1] \times [0, L-1] \times [0, L-1] \dots$, gives the multi-variables threshold segmentation using Convolutional function. The homogeneity of inputted image pixel is calculated and the similar characteristics of the pixel. The segment is classified according to the variant value.

The new modified parameters of the processed image are obtained. Here Kapur's and Otsu's methods are compared to apply multivariate threshold method to the classified pixels for the Convolutional values. where L is the grey level. The coordinate components of the optimum point are the thresholds. 3 thresholds in Otsu maximum variance (σ^2) segmentation for an 8-bit digital image correspond to the optimization to find the maximum (σ^2) in the space. If the coordinate of the optimum point is (t1,t2,t3), the three thresholds are (t1,t2,t3), respectively. For an L grey-level digital image G which is of NC Column NL row, its pixel number is NC xNL and grey-level set is {0,1,2,L-1}. The probability with a pixel having a grey level g_i is

$$P_i = \frac{g_i}{NC \times NL} \quad i \in \{0,1,2,L-1\} \quad \text{--- Eqn.4}$$

where pixels in image G are divided into K + 1 classes C0,C1,..., and Ck according to gray level with k thresholds t1,t2tk The grey level range of class C0 is [0,t0 - 1] , C1 is [t2,t1-1] and Ck is [tk,L-1]. The probability ω_i of a pixel belonging to the class C0 and the grey level probability mean μ_i of class C1 can be calculated as follows:

$$\omega_i = \sum_{j=t}^{t_i+j-1} P_j$$

$$\mu_i = \sum_{j=t}^{t_i+j-1} j * \frac{P_j}{\omega_i} \quad \dots \text{Eqn.12}$$

where $i=0,1,2,\dots,k$, $t_0=0$ $t_{k+1}=L$.

$$\mu = \sum_{i=t}^{t_{i+1}-1} i * P_i \quad \dots 13$$

The Otsu interclass variance [σ^2] is

$$\sigma^2 = \sum_{i=0}^k \omega_i * (\mu_i - \mu)^2 \quad \dots 14$$

The Kapur entropy value [ψ] is

$$\psi = - \sum_{i=0}^{t_1-1} \frac{P_i}{\omega_0} \ln \frac{P_i}{\omega_0} - \sum_{i=t_1}^{t_2-1} \frac{P_i}{\omega_1} \ln \frac{P_i}{\omega_1} - \dots - \sum_{i=t_k}^{L-1} \frac{P_i}{\omega_k} \ln \frac{P_i}{\omega_k} \quad \dots 15$$

The Otsu maximum between-class variance multilevel thresholding is to find the thresholds t1,t2tk . with which σ^2 is maximized, and the Kapur maximum entropy multilevel

thresholding is to find the thresholds t_1, t_2, \dots, t_k with which ψ is maximized.

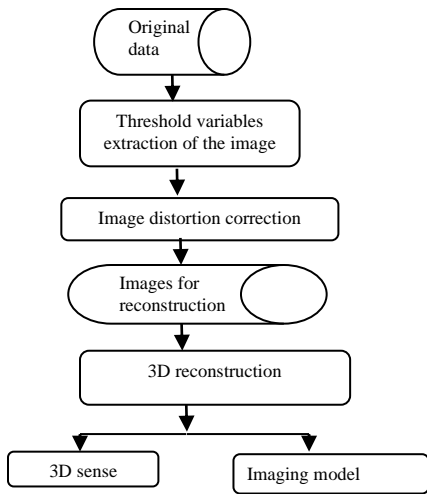


Figure 2.6. Extraction of parameters

2.4 Extraction of threshold parameters

The creation of threshold images from point of inflection of that specified interval. To evaluate the point of inflection for individual intervals, the Convolutional curve has been fitted on the individual data set (intervals), created after applying algorithm 2.1 is shown in figure 2.6. The point of the inflection point is considered as the threshold parameter for that particular interval. The point of inflection is the point where $G(x)=0$ and $G(x,y) \geq 0$ in each Convolutional fit curve. Each interval is converted into the binary image after applying the point of inflection as a threshold parameter. To receive one single threshold image, all the threshold images extracted from each interval are integrated as in figure 2.6,

2.5 Integrate the Threshold images

The integration of all the threshold images (T_1, T_2, \dots, T_n) has been done by using the union concept of image processing. Algorithm 3 explains the steps for creating an integrated image. Let the threshold images are $T_1, T_2, T_3, \dots, T_n$ then integrated image $I(0,1) = T_1 \cup T_2 \cup T_n$.

- 1: INPUT: Threshold Images T_1, T_2, \dots, T_6
- 2: OUTPUT: Integrated Threshold Image I
- 3: for $i \leftarrow 1$ to 6 do
- 4: $I = T_1 \cup T_2 \cup T_3 \cup T_4 \cup T_5 \cup T_6$;
- 5: end for

Algorithm 2,1 Algorithm for integrating threshold images

3. Experimental Analysis

Four different pixel classes are used to segment the images. The idea is to show the effectiveness of the algorithm and its performance against other algorithms solving the same task. The implementation can easily be transferred to cases with a greater number of pixel classes. To approach the histogram of an image by 4 Convolutional functions (one for each pixel class), it is necessary to calculate the optimum

values of the 3 parameters (P_i, μ_i and σ_i), for each Convolutional function (in this case, 12 values according to equation 2). This problem can be solved by optimizing equation 3, considering that function $p(x)$ gathers 4 Convolutional functions.

The parameters to be optimized are summarized in Table 3.1., with K_{p_i} being the parameter representing the a priori probability (P), K_{σ_i} holding the variance (σ) and K_{μ_i} representing the expected value (μ) of the Convolutional function i .

Parameters			Convolutional values
Prior probability, variance, value			I
K_{p1}	$K_{\mu1}$	$K_{\sigma1}$	1
K_{p2}	$K_{\mu2}$	$K_{\sigma2}$	2
K_{p3}	$K_{\mu3}$	$K_{\sigma3}$	3
K_{p4}	$K_{\mu4}$	$K_{\sigma4}$	4

Table 3.1. Parameters to be optimized by the Probability Algorithm

In the Threshold optimization, each parameter is considered like an Automaton which is able to choose actions. Such actions correspond to values assigned to the parameters by a probability distribution within the interval. All intervals considered in this work are defined as K_{P_i}



Figure 3.1. Segmented beam



Figure 3.2. Restructured segment

Figure 3.1 gives us the segmented beam, Figure 3.2 tells the threshold measures.

So the algorithm ignores this interval. to 1(m). the threshold values of various image segments Variables C_1, C_2, C_3 , and threshold σ then Convolutional fit p_i with the convergence values.

$BP = 4.93, A_1 = 0, K_1 = 1.74, A_2 = -0.129, K_2 = 2.38, R_{12} = 0.0035$ (insignificant), $R_{22} = 0.395$ (significant) and:

$Y_m = 1.74 \text{ t/ha}$ for $S_s < 4.93$ (breakpoint)

$Y_m = -0.129 S_s + 2.38 \text{ t/ha}$ for $S_s > 4.93$ (breakpoint)

indicating that beam salinities $< 4.93 \text{ dS/m}$ are safe and beam salinities $> 4.93 \text{ dS/m}$ reduce the yield @ 0.129 t/ha per unit increase of beam salinity.

Residual standard error: 18.8 on 10306 degrees of freedom
Multiple R-Squared: 0.997, Adjusted R-squared: 0.997

Convergence attained in 6 iterations with relative change - $9.592e-06$

The Estimated break even point is compared with the intercept point. The difference is found to be standard error. Thus the image segments with multivariate thresholds are calculated and tested. The density intervals are found to be feasible according to Convolution fit.

4. Conclusion

Conventional threshold models only contain partial threshold variable and only have limited applications when two or more threshold variables are needed. Thus far, little is known about the estimation of image segments in the beams with multiple threshold variables using Convolutional functions. This paper presents a new model that allows for more than one threshold variable. The selection of the threshold variables in this study is closely guided by the premises of the economical crisis models. The results found overwhelming evidence of threshold effects in the ratio of cracks found in beam concrete to reserve the measures of parameters collected from beam concrete and that lending rate differential. Finally, it should be mentioned that the applicability of the new model extends beyond the scope of economics. It can also serve as a foundation for further studies.

References

- Xiao Pang, Heming Jia, and Chunbo Lang," Modified dragonfly algorithm based multilevel thresholding method for color images segmentation", *Mathematical Biosciences and Engineering*, 16(2019): 6467–6511.
- Valentín Osuna-Enciso, Erik Cuevas and Humberto Sossa," A Comparison of Nature Inspired Algorithms for Multi-threshold Image Segmentation", *Centre for Investigation and Computation-IPN. Av. Revolución 1500, Guadalajara, Jal, México*.
- Dong Zhao, Lei Liu, Fanhua Yu, Ali Asghar Heidari, Mingjing Wang, Diego Olivae, Khan Muhammad, Huiling Chen," Ant colony optimization with horizontal and vertical crossover search: Fundamental visions for multi-threshold image segmentation", *Expert Systems With Applications xxx (XXXX) 114122*.
- B. H. Menze, A. Jakab, S. Bauer, J. Kalpathy-Cramer, K. Farahani, J. Kirby, Y. Burren, N. Porz, J. Slotboom, R. Wiest, L. Lanczi, E. Gerstner, M.-A. Weber, M. Prastawa, M. Reyes, and K. Van Leemput," The Multimodal Brain Tumor Image Segmentation Benchmark (BRATS)", *IEEE transactions on medical imaging*, vol. 34, no. 10, october 2015.
- Parul Dixit, Nidhi Tyagi 1 S," Optimization and analysis segmentation technique in image processing using matlab", *International journal of science and engineering*, vol 5.issue 4, April 2016.
- Amruta B. Patil , J.A.shaikh," OTSU Thresholding Method for Flower Image Segmentation", ISSN (e): 2250 – 3005 || Volume, 06 || Issue, 05||May – 2016
- Shiping Zhu, Xi Xia, Qingrong Zhang Kamel Belloulata," An Image Segmentation Algorithm in Image Processing Based on Threshold Segmentation", *Third International IEEE Conference 2007*.
- Juan Pablo Balarini, Sergio Nesmachnow," A C++ Implementation of Otsu's Image Segmentation Method", ISSN 2105{1232 c 2016 IPOL.
- Dong Zhao , Lei Liu , Fanhua Yu , Ali Asghar Heidari , Mingjing Wang, Guoxi Liang , Khan Muhammad, Huiling Chen," Chaotic random spare ant colony optimization for multi-threshold image segmentation of 2D Kapur entropy", *Knowledge-Based Systems · November 2020*.
- Saloni Khurana," Comparative Study on Threshold Techniques for Image Analysis", *International Journal of Engineering Research & Technology (IJERT)*, Vol. 4 Issue 06, June-2015.
- C.Mariyammal, S.Sasireka, "A Survey on Image Segmentation Methods", *IJARJSET*, Vol. 5, Issue 11, November 2018.
- Fahd M. A. Mohsen, Mohiy M. Hadhoud, Khalid Amin," A new Optimization-Based Image Segmentation method By Particle Swarm Optimization", (*IJACSA*), Special Issue on Image Processing and Analysis.
- Wenting Qiao, Xiaoguang Wu, Wen Sun³ and Qiande Wu," Research on Concrete Beam Crack Recognition Algorithm Based on Block Threshold Value Image Processing", DOI:10.32604/sdhm.2020.011479.
- Dr.A.Senthil Rajan," Segmentation in chick's image using artificial neural network", *International Journal of Advances in Computer Science & Its Applications – IJCSIA*, Volume 9 : Issue 1- [ISSN : 2250-3765] - Publication Date: 10 May, 2019.
- Dr.A.Senthil Rajan," Segmentation in Manganethi Plant using Mathematical Morphology", *International Journal of Advanced Research in Computer and Communication Engineering (IJARCCE)*, Vol – 6, Issue – 10, ISSN 2278-1021, Impact Factor: 5.947, Page: 291-293, October 2017.