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An Evaluation of Two Mammography Segmentation Techniques

Sujata[1], R. B. Dubey[2], R. Dhiman[3], T. J. Singh Chugh[4]
EE, DCRUST, Murthal, Sonepat, India[1, 3]
ECE, Hindu College of Engineering, Sonepat,India[2]
ECE department, GIET, Sonepat, India[4]

Abstract

Mammographic mass detection is an important task for early detection of breast cancer diagnosis and treatment. This is however still remains a challenging task. In this paper, we have proposed a multilevel thresholding algorithm for segmenting the tumor. This paper compares two most popular method, namely between class variance (Otsu) and entropy criterion (Kapur's) methods for segmenting the tumor. Our algorithms are tested on 20 mammograms and showing promising results.

Keywords

Breast cancer, multilevel thresholding, segmentation, Otsu's method, Kapur's method

1. Introduction

Breast cancer is the second-most common and leading cause of cancer death among women [1]. Segmentation subdivides an image into different regions or objects based on the information found about objects in imaging data. In the segmentation of medical images, the objective is to identify different regions, organ and anatomical structure from data acquired via MRI or other medical imaging technique [2]. Initially segmentation has been done based manually by human experts. But manually segmentation is a difficult and time consuming task which makes automated breast cancer segmentation desirable [2]. Thresholding is a popular tool for image segmentation for its simplicity, especially in the fields where real time processing is needed [3]. Many threshold selection methods are based on gray histogram, the maximum between class variance methods proposed by Otsu [4] becomes widely used in image processing for its better segmentation results, easy computation and wide scope of application [5].However, the problem gets more and more complex when we try to achieve segmentation with greater detail by employing multilevel thresholding. Usually it is not simple to determine exact locations of distinct valleys in a multimodal histogram of an image, that can segment the image efficiently and hence the problem of multilevel thresholding is regarded as an important area of research interest among the research communities.

Histogram thresholding is one of the very basic and popular techniques used for segmentation. This is due to its robustness, accuracy and simplicity. A single threshold classifies an image into two groups. Thus multiple thresholds can classify the image into more than two groups i.e. if there are N threshold values then image will be classified into (N+1) groups [7]. Now, the selection of thresholding involves intelligence and optimization so that these groups represent large cluster of pixels that share similar intensity values thus segmenting significant objects. In other words, pixels belonging to same object have similar intensities so if we can label the pixels according to this criterion then we can place these pixels in one class. However, unlike all the segmentation techniques, histogram threshold also fail when there is low contrast and poor illumination; because this results in partial segmentation or sometimes include false positive pixels in segmentation [7]. Especially if the object of interest has multiple colours, bi-level segmentation can have high false negative rate [7]. The rest of this paper is organized as follows: In Section 2, details of methodology are formulated. Section 3 deals with the results and discussion. Finally, the concluding remarks are given in Section 4.

2. Methodology

Entropy criterion method (Kapur's)

Entropy criterion, as proposed by Kapur et al. [6], has been popularly employed in determining whether the optimal thresholding method can provide histogram-based image segmentation with satisfactory desired characteristics [3]. The original algorithm in Kapur et al. [6] has been developed for bi-level thresholding and can be described as follows. Let there be gray levels in a given image and these gray levels are in the range {0, 1, 2… (L-1)} .Then one can define$P_i = h(i)/N$, $(0 \leq i \leq (L-1))$ where $h(i)$ denotes number of pixels with gray level i and N

denotes total number of pixels in the image $= \sum_{i=0}^{L-1} h(i)$[3]. Then, the objective is to maximize a fitness function

$f(t) = H_0 + H_1$ (1)

$H_0 = -\sum_{i=0}^{t1-1} \frac{p_i}{w_0} ln \frac{p_i}{w_0}$, $w_0 = \sum_{i=0}^{t1-1} p_i$ and

$H_1 = -\sum_{i=t}^{L-1} \frac{p_i}{w_1} ln \frac{p_i}{w_1}$, $w_1 = \sum_{i=t}^{L-1} p_i$

This method has later been extended to solve multilevel thresholding and describe as follows: The optimal multilevel thresholding problem is treated as an m-dimensional optimization problem, for determination of m optimal thresholds for a given image $[t_1, t_2 \dots t_m]$, where the aim is to maximize the following objective function

$$f([t_1, t_2 \dots . t_m]) = H_0 + H_1 + H_2 + \cdots . H_m$$

(2)

Where,

$$H_0 = -\sum_{i=0}^{t_1-1} \frac{p_i}{w_0} ln \frac{p_i}{w_0}, \quad w_0 = \sum_{i=0}^{t_1-1} p_i$$

$$H_1 = -\sum_{i=t_1}^{t_2-1} \frac{p_i}{w_1} ln \frac{p_i}{w_1}, \quad w_1 = \sum_{i=t_1}^{t_2-1} p_i$$

$$H_2 = -\sum_{i=t_2}^{t_3-1} \frac{p_i}{w_2} ln \frac{p_i}{w_2}, \quad w_2 = \sum_{i-t_2}^{t_3-1} p_i \dots .$$

$$H_m = -\sum_{i=t_m}^{L-1} \frac{p_i}{w_m} ln \frac{p_i}{w_m}, \quad w_m = \sum_{i=t_m}^{L-1} p_i$$

Between class variance methods (Otsu)

The between-class variance method, as proposed by Otsu [4], is used to determine the threshold values, which maximize the between-class variance to separate the segmented classes as farther as possible. Otsu method is a non-parametric approach for global histogram thresholding. It was developed to calculate optimal threshold from image histogram using between class variance criteria. [7]

2.1 Bi-level thresholding

In bi-level thresholding, an image is divided into two classes, C_0 andC_1, by a threshold at a level t, class C_0 contains the gray levels from 0 to t-1 and class C_1 consists of the other gray levels with t to L-1 [8]. Then, the gray level probabilities (w_0(t) and w_1(t)) distributions for the two classes are as follows. Mean levels μ_0 and μ_1 for classes C_0 and C_1 are

$$\mu_0 = \sum_{i=0}^{t-1} \frac{i \times p_i}{w_0(t)}$$

$$\mu_1 = \sum_{i=1}^{L-1} \frac{i \times p_i}{w_1(t)}$$

Let μ_T be the mean intensity for the whole image, it is easy to show that

$w_0\mu_0 + w_1\mu_1 = \mu_T$ and

$w_0 + w_1 = 1$

The objective function can be defined as follows

Maximize $f(t) = \sigma_0 + \sigma_1$

where

$\sigma_0 = w_o(\mu_0 + \mu_T)^2$ *and*

$\sigma_1 = w_1(\mu_1 - \mu_T)^2$

2.2 Multilevel thresholding

The method can also extend to solve multilevel thresholding problem as follows: Assuming that there are m thresholds, (t_1), which divide the original image into m classes: C_0 for [0...$t_1 - 1$], C_1 for [t_1…$t_2 - 1$]… and C_m for [t_m,…,L-1], the optimal thresholds are chosen by maximizing the following equation

$$f(t) = \sigma_0 + \sigma_1 + \sigma_2 + \cdots \sigma_m \quad (3)$$

where,

$$\sigma_0 = w_0(\mu_0 - \mu_T)^2,$$
$$\sigma_1 = w_1(\mu_1 - \mu_T)^2,$$
$$\sigma_2 = w_2(\mu_2 - \mu_T)^2,$$
$$\sigma_m = w_m(\mu_m - \mu_T)^2,$$

3. Results and Discussions

Proposed algorithms are demonstrated by considering 20 mammogram images that show positive for malignant mass. Otsu method chooses the optimal threshold by maximizing the between-class variance of gray levels. Kapur's find the optimal threshold values based on the maximizing of the entropy of the histogram. These approaches are simple and effective in bi-level thresholding and further extend to multilevel thresholding. Fig.1, Fig.2, Fig.3, Fig.4 and Fig.5 shows the original mammogram images from data base, the gray scale images, the histogram for Otsu method, the segmentation result for ostu method and extracted ROI for Otsu methods respectively. Further Fig.6, Fig.7 and Fig.8 show the histogram for Kapur method, the segmentation result for Kapur method and extracted ROI for Kapur method respectively. The comparisons of results for both methods are given in table1 and table 2.

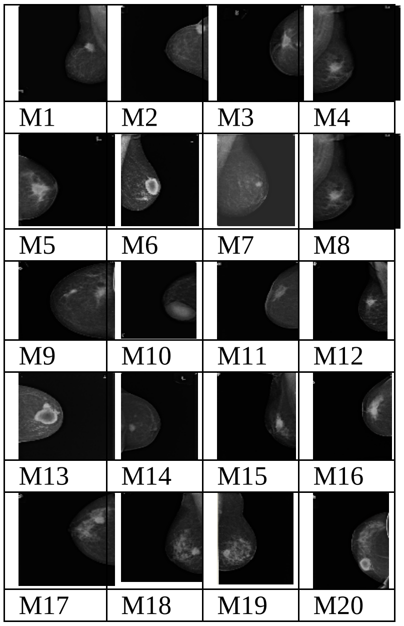


Figure 1: Original images

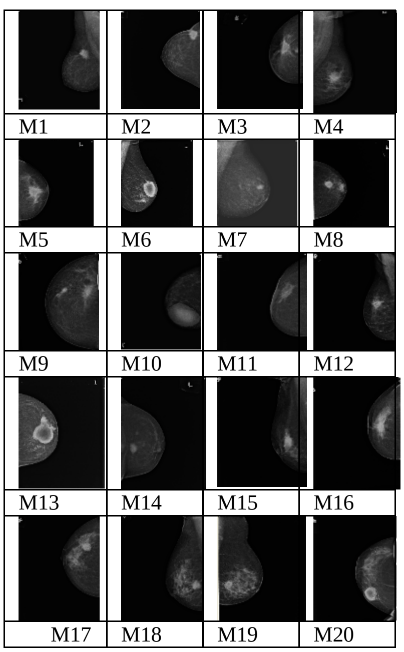
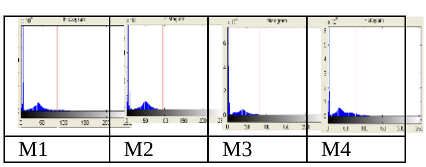


Figure 2: Gray scale images



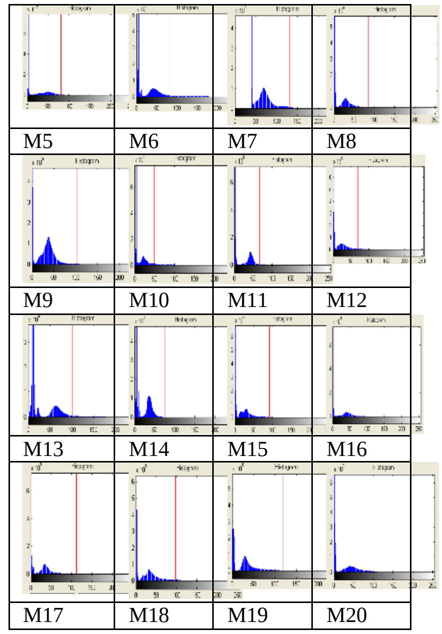


Figure 3: Histogram for Otsu method

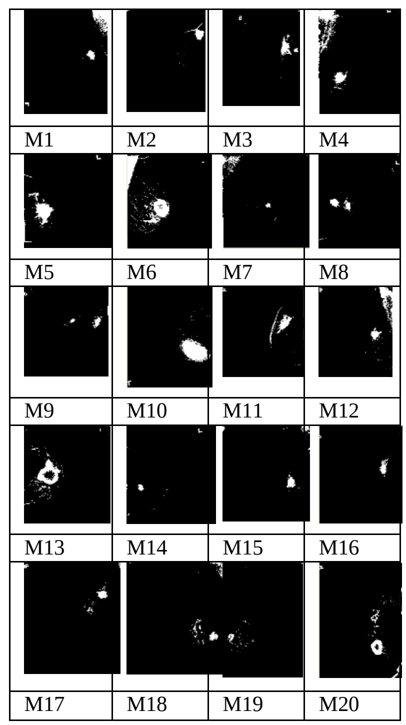
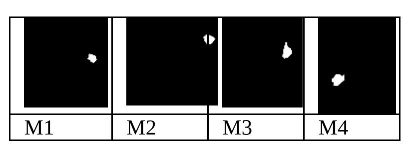


Figure 4: Segmented image for Otsu



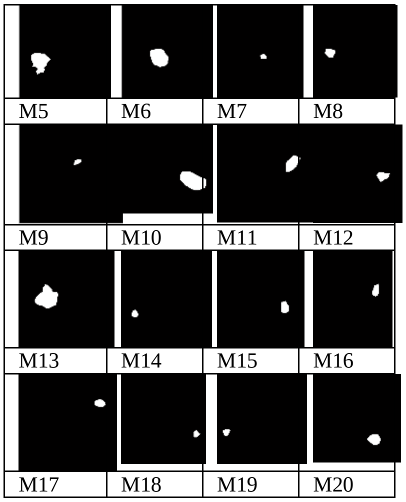


Figure 5: Extracted ROI for Otsu

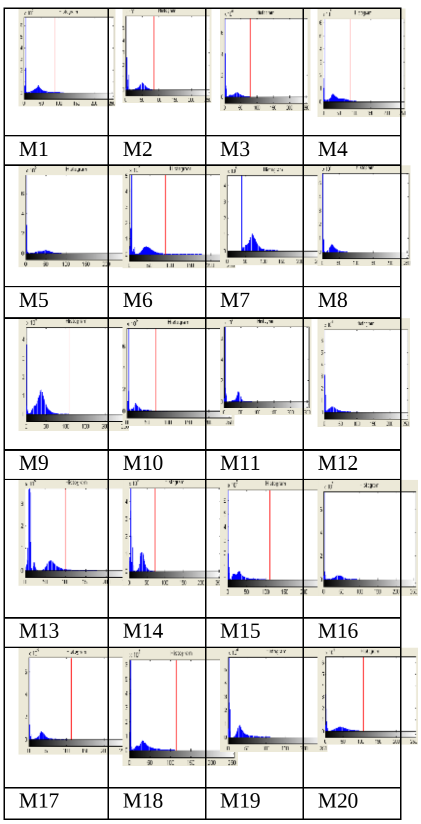
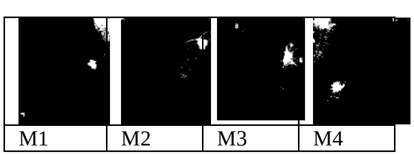


Figure 6: Histogram for Kapur's method



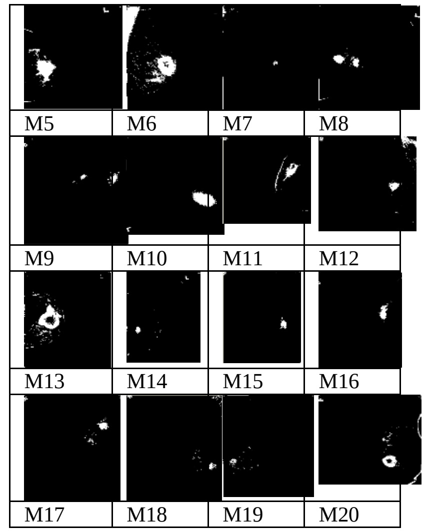


Figure 7: Segmented image for Kapur's method

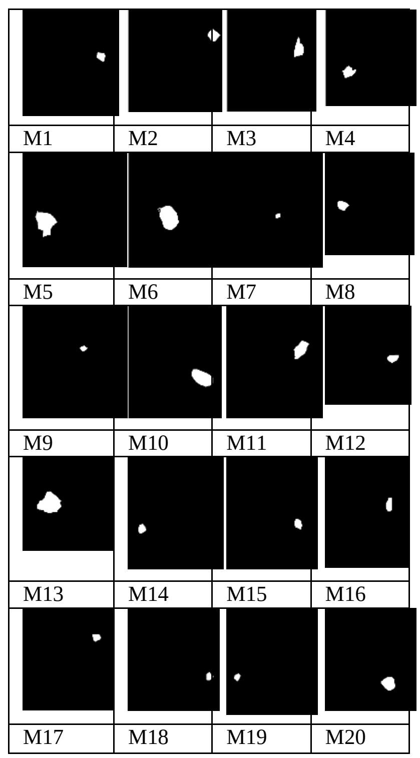


Figure 8: Extracted ROI for Kapur's method

Table 1: Various characteristics of segmented ROIs using Ostu method

S. No.	Area (cm^2)	Major axis length (*mm*)	Minor Axis Length (*mm*)	Eccen-tricity	Soli-dity	Perim-eter (*mm*)
M1	0.75	33.10	25.11	0. 56	0. 91	105.39
M2	1.05	36.11	31.65	0. 48	0. 96	113.53
M3	1.31	48.14	32.25	0.74	0.90	149.29
M4	1.46	50.04	32.68	0. 75	0.88	165.78
M5	3.15	66.46	55.45	0. 55	0. 87	233.13
M6	3.13	64.92	51.877	0. 60	0. 97	195.78
M7	0.33	22.49	15.85	0. 70	0. 94	68.28
M8	0. 95	35.49	29.40	0. 56	0.97	107.84
M9	0.31	24.59	14.22	0.81	0. 93	65.21
M10	4.43	93.38	51.34	0.83	0. 97	245.37
M11	1.65	57.40	31.14	0. 84	0.97	151.78
M12	1.01	41.39	27.68	0.74	0.93	118.56
M13	3.96	69.69	64.62	0.37	0.91	248.93
M14	0.43	22.50	21.01	0.35	0.97	71.35
M15	0.94	37.38	27.96	0.66	0.95	109.94
M16	0.83	39.78	22.93	0.81	0.93	107.59
M17	0.68	33.12	22.16	0.74	0.97	90.18
M18	0.56	27.19	22.43	0.56	0.95	83.11
M19	0.45	23.83	21.23	0.45	0.96	75.11
M20	1.43	42.46	36.57	0.50	0.98	130.71

Table 2: Various characteristics of segmented ROIs using Kapur's method

S. No.	Area (cm^2)	Major axis length (*mm*)	Minor Axis Length (*mm*)	Eccen-ricity	Soli-dity	Perim-eter (*mm*)
M1	0.59	29.54	22.47	0.64	0.95	89.59
M2	0.050	35.63	32.42	0.41	0.96	113.68
M3	1.37	51.96	31.96	0.78	0.89	157.74
M4	1.168	41.63	32.24	0.63	0.87	150.61
M5	2.86	3.72	52.52	0.56	0.84	223.58
M6	2.86	64.32	48.10	0.66	0.97	191.29
M7	0.17	16.49	11.80	0.69	0.93	46.72
M8	0.87	36.81	26.42	0.69	0.94	109.98
M9	0.24	19.97	13.64	0.73	0.96	56.76
M10	2.20	69.74	34.10	0.87	0.96	178.02
M11	1.57	56.15	30.79	0.83	0.92	156.50
M12	0.77	40.49	21.37	0.84	0.96	105.25
M13	4.166	74.55	63.15	0.53	0.91	249.52
M14	0.529	24.75	23.34	0.33	0.96	80.42
M15	0.586	28.54	22.31	0.62	0.96	83.69
M16	0.796	37.29	23.13	0.78	0.97	99.35
M17	0.534	27.42	21.50	0.62	0.95	81.94
M18	0.435	22.91	21.48	0.34	0.93	75.01
M19	0.344	21.43	17.57	0.57	0.94	65.01
M20	1.58	44.45	38.88	0.48	0.97	137.53

4. Conclusions

The proposed multilevel thresholding algorithm provides satisfactory result with manually selected threshold values for segmenting breast cancer. The work devoted to segment the mammogram images, which would facilitate in clinical decision making and diagnosis. Otsu and Kapur's methods [6] have been confirmed as an efficient method for bi-level thresholding in image segmentation .However when these method are extend to multilevel thresholding, suffers from the problem of long durated processing time and computation time. Further work is in progress to extend multilevel thresholding Otsu and Kapur's method for segmentation of tumor using bacterial foraging.

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Sujata Bhatia was born on 21st October 1987. She received her B. Tec. degree in biomedical engineering from Guru Jambheswar University of science and technology, India 2010 and pursuing M. Tech. in Instrumentation and Control from DCRUST, Murthal, Sonepat, India.

Rash Bihari Dubey was born in India on 10th November 1961. He received the M. Sc. degree in Physics with specialization in Electronics in 1984 from Agra University Agra, India, the M. Tech. degree in Instrumentation from R.E.C. Kurukshetra, India in 1989 and the Ph.D. degree in Electronics Enggg., from M. D. University, Rohtak, India in 2011. He is at present Professor and Head in the Department of Electronics and Communication Engineering at Hindu College of Engineering, Sonepat, India. He has well over 40 publications in both conferences and journals to his credit His research interest are in the areas of Medical Imaging, Digital Signal Processing, Digital Image Processing, Biomedical Signal Analysis, and Industrial Real Time Applications.

Rohtas Dhiman was born on 27th Dec 1975. He completed his B. E. (1998) and M. E. (2008) degrees from C. R. State College of Engineering, Murtahl, Sonipat, India. Currently he is assistant professor in electrical engineering department at D. C. R. University of science and technology Murtahl, Sonipat, India, and pursuing Doctoral degree from the same university. His current area of interest includes biomedical signal processing, intelligent techniques, brain computer interface, genetic algorithms, bio-inspired optimization techniques, machine vision and image processing.

Tarun Jeet Singh Chugh was born on 14th July 1987. He received his B.E. degree in Electronics and Communication Engineering from M. D. U., Rohtak in 2009 and M. Tech. Degree in Electronics and Communication Engineering from M. D. U., Rohtak. Currently he is working as a lecturer in the Department of Electronics and Communication Engineering, SGI, Samelakha, Panipat, Haryana, India.