Journal of Theoretical and Applied Information Technology
20th January 2016. Vol.83. No.2

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

# IMPROVING MULTILEVEL THRESHOLDING ALGORITHM USING ULTRAFUZZINESS OPTIMIZATION BASED ON TYPE-II GAUSSIAN FUZZY SETS

**SHOFWATUL 'UYUN**
Department of Informatics, Faculty of Science and Technology
Sunan Kalijaga State Islamic University, Yogyakarta
E-mail: shofwatul.uyun@uin-suka.ac.id

**ABSTRACT**

Image thresholding is one of image processing techniques to help analyze the next phase. Consequently, choosing a precise method in this step is quite-essential. Image blurs and bad illumination are common constraints that often influence the effectiveness of the thresholding method. Fuzzy sets is one among other perceptions in scoring an image. Thus, various thresholding fuzzy techniques have been developed to eliminate those constraints. This paper proposes the improvement of multilevel thresholding techniques by using type II fuzzy sets with the function of gaussian membership to access some objects at mammogram to get fibroglandular tissue areas. The result shows that the proposed technique has a very good achievement with the average score with misclassification error parameter of 97.86%. This proves that the proposed algorithm are able to function well to the image with low contrast level and high unclearness level.

**Keywords:** *Multilevel Thresholding, Ultrafuzziness, Fuzzy Sets, Type II, Gaussian*

## 1. INTRODUCTION

Segmenting process is one of the important phases in analyzing images. Other tools include several system applications; such as pattern recognition, computer vision, and especially digital image processing [1-4]. The objective of image segmentation process is to separate objects from their backgrounds, and with formerly separated elements of objects within images-elements within the objects which were separated in the previous process/step- so that analysis process can be done. Generally, image segmentation process methods consist of two types; based on regions and based on thresholds. Regional based segmentation process is used to divide images based on homogeneity criteria [5]. The results by using this segmenting process method are often unsatisfying. This is because it is difficult to determine the precise types and numbers of criteria to be applied at some different regions in the segmenting areas. In addition, the second approach of segmenting process method is called the thresholding which are done by using thresholds based on characteristics of the histogram. The thresholding method is a method of segmenting process which is effective and is applied very often in image processing. Another advantage of this method is its simplicity and implementability [6].

The thresholding methods are generally divided into two types; the bi-level one and the multi-level one. Bi-level approach classifies pixels and images into two classes, and multilevel approach classifies into several classes based on intensity scores of pixels. Multilevel thresholding process has more difficult and complicated tasks compared to bilevel thresholding process. Some algorithm used in thresholding segmentation process include global thresholding, adaptive thresholding, p-tile thresholding, maximum entropy and multi-otsu thresholding. Fuzzy image processing is a group of various fuzzy approaches for image processing that includes image representing and processing by dividing an image into several parts and characteristics as fuzzy sets [7]. There are four important reasons related to the use of fuzzy image processing; *firstly*, some fuzzy techniques are powerful tools for representing and processing of complex knowledge; *secondly*, it has ability to deal with unclarity and ambiguity efficiently; *thirdly*, there is grayed ambiguity of images; and *fourthly*, it is geometrical fuzziness. In general, the theoretical approach of fuzzy sets consists of fuzzy sets type I and type II [8].

The weakness of using type I is the need to define some parameters related to the membership function, variable and the fuzzy collection based on

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

experts' knowledge. Therefore, the use of type II (ultra-fuzzy sets) is required to eliminate the uncertainty resulted from employing fuzzy type I. Some previous researches have applied the type II for segmenting process based on bi-level thresholding, such as [9-12]. Apart from being examined in multimedia images, the objectives include to improve medical images, such as laser images [9], teeth images [10], x-ray images [12] and mammogram images [11]. In determining the top and the bottom limits of type II fuzzy sets, previous researches still applied manual setting which is static. Some types of fuzzy membership have been used, for example sigmoid [9-10,12], gaussian [12]. Apart from using sigmoid membership functions, [10] added other membership functions as well, those are triangular, trapezoidal and Z with the score at hedge linguistic parameters of 1, 2, 3, 10 and 25. In general, the testing results based on error misclassification parameters [9,10, 12] and Jaccard index [12] showed that thresholding algorithms using type II fuzzy sets were more effective. [10] has compared type II fuzzy sets with type I fuzzy sets, Otsu and Kitler.

Thus, this paper proposes algorithm improvement for multilevel thresholding using ultrafuzziness of type II fuzzy sets for gaussian membership functions. Even though the proposed algorithm is allocated to multi-level, in the examining phase, however, bi-level would be applied. The used images are multimedia images and mammogram images. Mammogram images have been employed by [11] for thresholding process using type II fuzzy sets with bi-level for cluster microcalcification detection. The mammogram images used in this research have different objectives from those done by [11], that is to get fibroglandular as one of indicators to classify breast cancer risks factors [13].

The remainder of this paper is organized as follows. In Section 2, Image thresholding based using ultra fuzziness of type II fuzzy set is explained. In addition, the detailed procedure of the proposed method is introduced in Section 3. Furthermore, Section 4 presents the result and discussion using multimedia image for bilevel thresholding and mammogram image for multilevel thresholding. Finally, the conclusions are drawn in Section 5.

## 2. IMAGE THRESHOLDING BASED USING ULTRA FUZZINESS OF TYPE II FUZZY SET

One of image segmentation process methods popularly used is foreground and background determination of images based on limited scores, so that intensity score of images are set to be two scores; 0 for black, and 1 for white. Fuzziness is an approach that can be applied to determine threshold scores in which the score of an image is as fuzzy sets. The next question is how many fuzzy images being processed to make segmentation. This could not be separated from the process of determining membership function from each fuzzy set at a variable. In addition, determining top and bottom limits from each membership function has a very important role. There are various ways to determine the limits, including experts' knowledge and the result of clustering process (i.e. subtractive clustering).

The most common way to determine fuzziness is by using linear index from the fuzziness [14]. For the image M x N subset A⊆ $X$ with greyness degree L, $g \in |0, L-1|$, histogram h (g) and membership function $\mu_x(g)$, the score of fuzziness linear index $\gamma_i$ is counted by the following formula (1)

$$\gamma_i(A) = \frac{2}{MN}\sum_{i=1}^{M-1}\sum_{j=1}^{N-1}\min\left[\mu_A(g_{ij}), 1-\left[\mu_A(g_{ij})\right]\right] \quad (1)$$

Nevertheless, it is often difficult to determine the parameter of the fuzzy sets, whether a certain datum includes in a fuzzy set or not, especially at the condition with the membership degree of 0,5 as shown in the Figure 1. Therefore, some weaknesses found in the type I fuzzy sets are improved in the type II. The proposed concept is designed by using three dimensional membership functions, each dimension in type II has a membership ranging of (0, 1). Furthermore, the scores of those three dimensions are an extension or an addition of membership degrees to attain further information representing fuzzy sets. The type II fuzzy sets is quite useful when it is difficult to determine fuzzy set function membership in an ambiguous case.

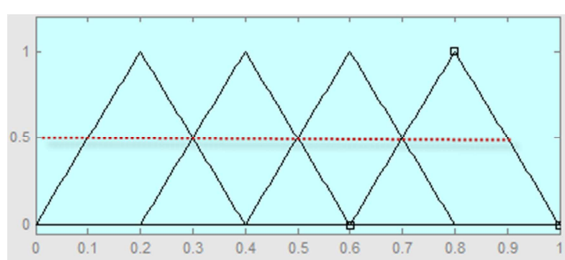


*Figure 1. Fuzziness Scale Representation*

Figure 2 and 3 show the differences of both types in membership functions. Fuzzy sets type II have score limits defined as lower and upper

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

membership functions. Both functions define upper and lower memberships in each score of horizontal line. Figure 4 is an interval score example from type II fuzzy sets (A(a) = $[\alpha_1, \alpha_2]$), where $\alpha_1$ is the score of lower membership and $\alpha_2$ is the score of upper membership. Meanwhile, the difference of membership score counting between type I and type II is shown in Figure 5.

If the fuzziness degree at the highest level, the division of image data ambiguity at gradient would be high as well and would be led to the difficulty in determining the limit of the scores. In the type II, fuzziness degree is determined by ultrafuzziness scoring, using membership function from $\alpha_1$ (lower) and $\alpha_2$ (upper) which is called footprint of uncertainty (FOU) shown as the grey area (Figure 3-5). Scoring determinantion from ultrafuzziness index (UF), used the formula (2) [9].

$$UF = \frac{1}{N}\sum_{min}^{max} h(x)[\mu_U(x) - \mu_L(x)] \quad (2)$$

N is the total number of histogram pixel, min and max are minimum and maximum score on histogram,

X axis is a grey scoring that appears in histogram, whereas h(x) is the number of score graylevel on the histogram. Some upper and lower membership functions are constructed using hedge operator ($\alpha$) at basic membership function of skeleton ($\mu(x)$) that is shown at the formula (3) and (4).

$$\mu_U(x) = [\mu(x)]^{1/\alpha} \quad (3)$$

$$\mu_L(x) = [\mu(x)]^{\alpha} \quad (4)$$

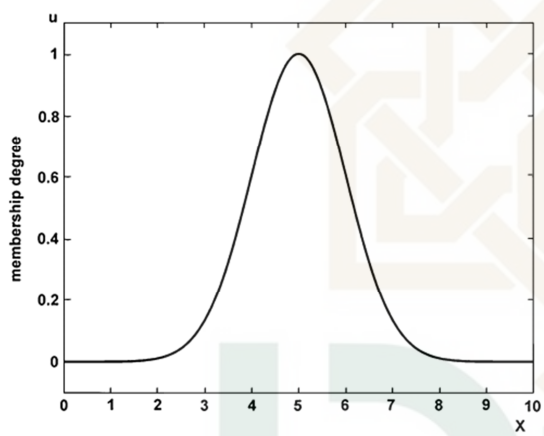


*Figure 2. An Example of Membership Function Type I*

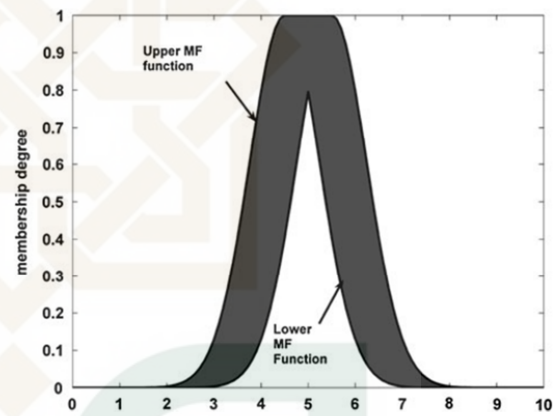


*Figure 3. An Example of Membership Function Interval of The Type II*

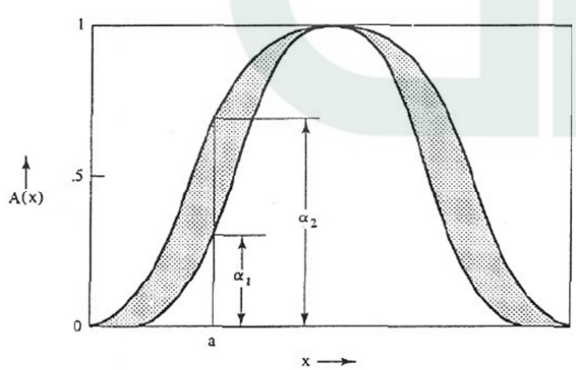


*Figure 4. An Example of Scoring Interval From Fuzzy Set (A(a) = $[\alpha_1, \alpha_2]$)*

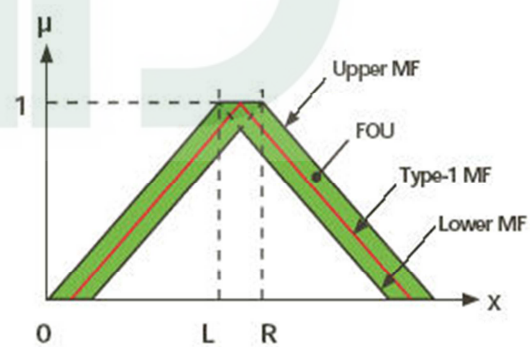


*Figure 5. The Difference Between Type I and Type II, (Upper MF and Lower MF)*

## 3. THE PROPOSED METHOD

The proposed algorithm in this paper is for multilevel thresholding based on ultafuzziness optimization in type II fuzzy sets using gaussian membership functions which are scrutinized as follows:

a) Counting image histogram

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

b) Summing up the mean ($\mu$) and standard deviation ($s$) of images
c) Determining the number of levels (i.e. there are three levels to separate images into four objects)
d) Counting the score of membership in each greyness degree using the gaussian function with (5) formula

$$f(x;\sigma,c) = e^{\frac{-(x-c)^2}{2\sigma^2}} \quad (5)$$

In which:

$\sigma$ = Sigma
c = culminating point

e) Measuring the culminating point (c) to $c_1$, $c_2$, and $c_3$ with the number of level 3

If level = 1 then
$c_1 = \mu$
Else
if level = 2 then
$c_1 = \mu - s$
$c_2 = \mu + s$
Else
$c_1 = \mu - s$
$c_2 = \mu$
$c_3 = \mu + s$

f) Calculating the membership of upper ($\mu_U(x)$) and lower ($\mu_L(x)$) every position using the formula of (3) and (4)
g) Summing up ultrafuzziness (UF) at every datum point using the formula of (2)
h) Finding the membership score at every datum point with the most optimum ultrafuzziness score at each level
i) Using ultrafuzziness optimum score as threshold scores at every level to separate objects in the images; in this case, there are three threshold scores.

## 4. RESULT AND DISCUSSION

The techniques proposed in this paper were examined for thresholding processes, using both unilevel and multilevel which are shown in the Figure 6, 7 and 8. For one-level thresholding, experiments were conducted to several images with the sigma parameter ($\sigma$) which is different, with 1, 5 and 10. The thresholding result based on the use of different sigma parameters shown in Figure 6 and 7. Using the parameters $\sigma$ gave an influence on the resulted thresholding score, having positive correlation in which the higher the score $\sigma$, the higher threshold score is. The resulted images of thresholding with the smallest score $\sigma$ can produce better binary images.

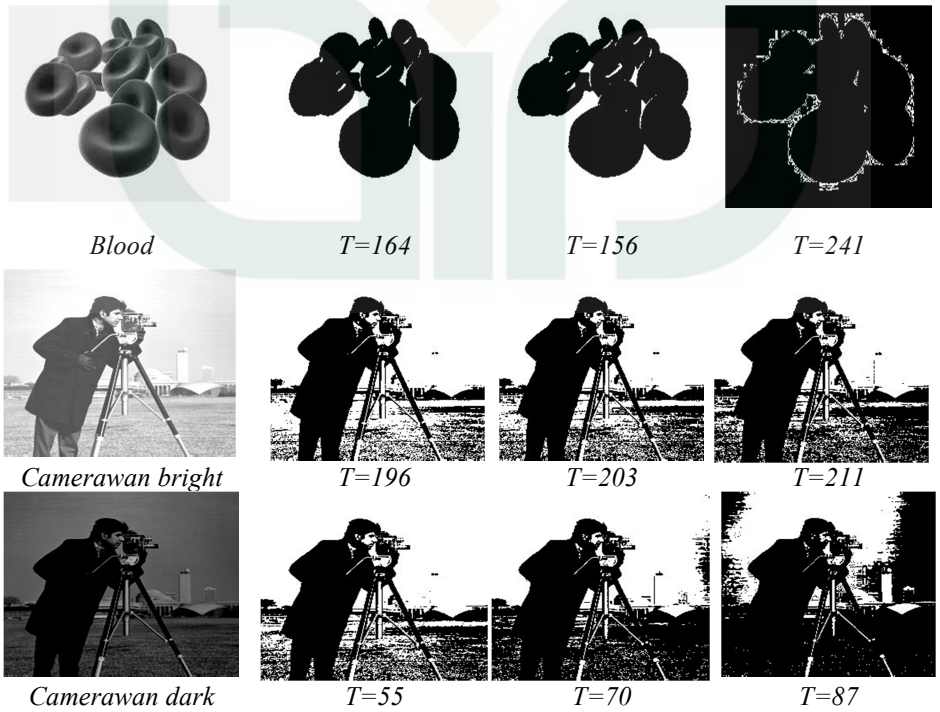


*Figure 6. The Thresholding Result Using The Proposed Technique With One-Level Using Sigma*

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

*Parameter 0:1,5 And 10*

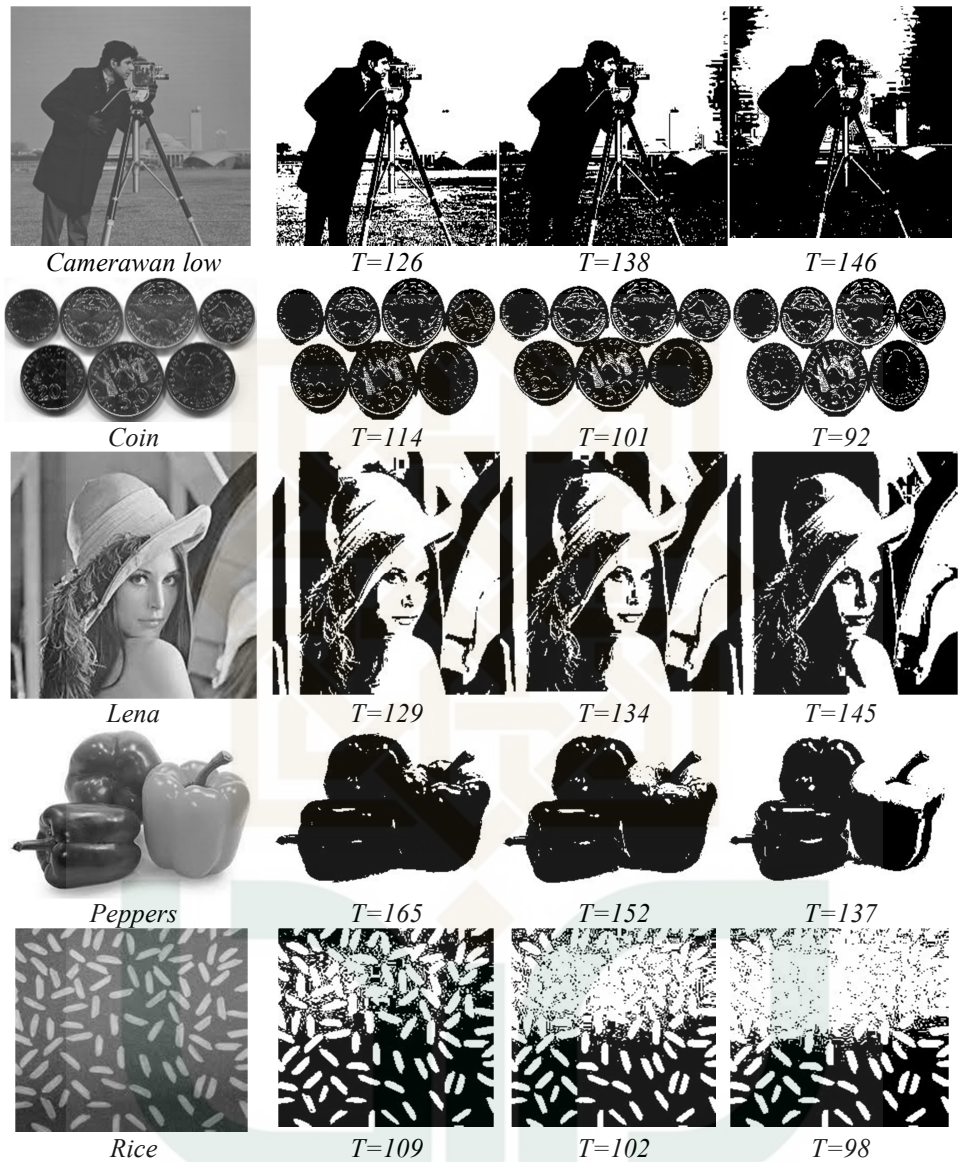


*Figure 7. The Thresholding Result Using The Proposed Technique With One-Level Using Sigma Parameter 0:1,5 And 10*

The proposed algorithm was examined as well in mammogram images with cranio caudal views using multilevel thresholding to gain fibroglandular areas that can represent the risk factors of breast cancers using the standard of BI-RADS based on mammography density percentage. In this research, the mammography segmenting process is divided into four areas; uncompressed fatty tissues, fatty tissues, non-uniform density tissues, and high-density tissues. The uncompressed fatty tissues are fat tissues located at breast edges. Fatty tissues are fat tissues located between uncompressed fatty tissues and the solid tissues surrounding. Non-uniform density tissues are part of density tissues surrounding the tissues that have higher density, commonly known as fibroglandular tissues. Therefore, segmenting process using three level algorithm thresholding is required. The result of a similar mammogram image thresholding with the sigma score ($\sigma$) which is different: 1,5 and 10 as shown in the Figure 8 to access fibroglandular areas using third threshold score. As an example for the first mammogram (located on the top in the picture), the fibroglandular area is resulted from segmenting process with third index of thresholding applying threshold score 119. The best result is by using sigma score 1.

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

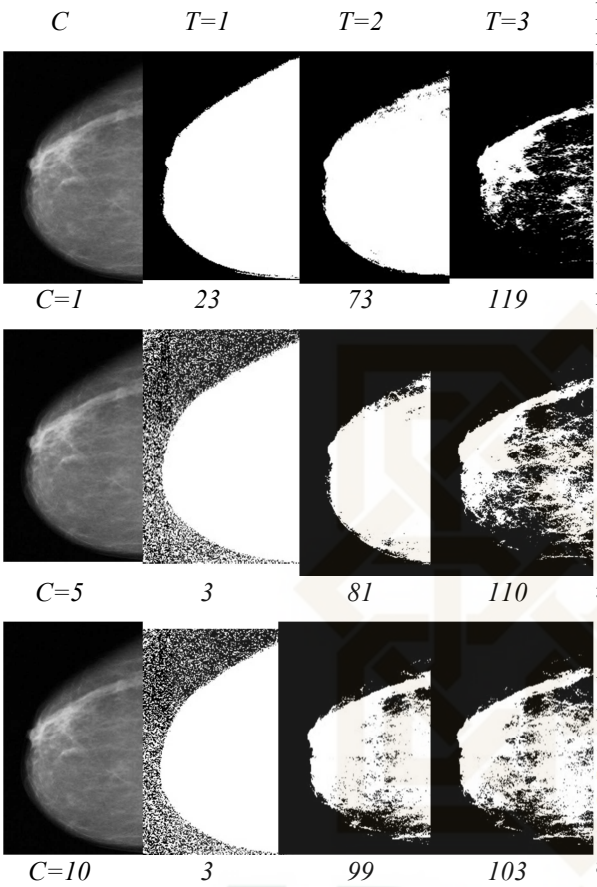


*Figure 8. The Threshoding Result Using The Proposing Techniques With Multi-Levels Using Sigma Parameter (σ): 1,5 and 10.*

To examine the effectiveness of the proposed algorithm in this paper, the test by using multi-level thresholding in mammogram images to gain fibroglandular tissues area was conducted. The used parameter of this paper which aims at measuring the effectiveness of a thresholding algorithm is called misclassification error ($\eta$) [15] shown in formula 6.

$$\eta = 100\ X - \frac{|B_0 \cap B_T| + |F_0 \cap F_T|}{B_0 + F_0} \qquad (6)$$

$\eta$ is a correlated representation between images resulted from segmenting process by using thresholding algorithm and using semi-automatic thresholding by Radiologists (for the case of mammogram image). $B_0$ and $F_0$ are the number of pixels as the background and the foreground in binary images of thresholding determined by Radiologists. Meanwhile, for $B_T$ and $F_T$ show the number of pixels as the background and the foreground in the resulted binary image using threshold score done by algorithm thresholding process. The resulted score for $\eta$ represents the right pixels in which the higher the score, the higher the effectiveness level of the thresholding algorithm.

To find the effectiveness of the proposed algorithm, an experiment to the same image by using some different thresholding algorithm; type II fuzzy sets, type I fuzzy sets, multi-otsu thresholding, max enthropy and moments. The resulted binary image from the segmenting process of some thresholding algorithm was then calculated its error miscalculation score. The more detail result is shown in Table 1. The proposed algorithm has the highest average score of 97,86%, with the smallest deviation standard of 2,71%. On the contrary, the lowest average score is 79,36% with the biggest deviation standard of 13,09%.

## 5. CONCLUSION

The proposed algorithm is the improvement version of type II fuzzy sets that is proven to be more effective from fuzzy sets both type I and type II. It is shown by its average score of the biggest error misclassification parameter, counted for 97,86% and the lowest deviation standard, counted for 2,71% if compared with some other thresholding algorithms. In addition, the algorithm is able to generate threshold score automatically, in line with the examined image characteristics, in this case by using mammogram image which is one of image types with a very low contrasting level and with a very high blur level. Further research is needed to perfect the proposed method. An improvement of a better membership function design will greatly contribute to gain a better thresholding method such as Pi function and Vicinity function.

## ACKNOWLEDGMENT

The author extend their sincere thanks to Dr. dr. Lina Choridah, Sp.Rad(K) , a senior radiologist for breast cancer at Oncology Clinic; for providing necessary support and guidance throughout the research work and furthermore for the Research Institution of State Islamic University Sunan Kalijaga for research funding.

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

**REFERENCES:**

[1] N. Al-Najdawi, M. Biltawi, and S. Tedmori, "Mammogram image visual enhancement, mass segmentation and classification", *Applied Soft Computing,* Vol. 35, 2015, pp. 175-185.

[2] B. L. DeCost and E. A. Holm, "A computer vision approach for automated analysis and classification of microstructural image data", *Computational Materials Science,* Vol. 110, 2015, pp. 126-133.

[3] M. Y. Potrus, U. K. Ngah and B. S. Ahmed, "An evolutionary harmony search algorithm with dominant point detection for recognition-based segmentation of online Arabic text recognition", *Ain Shams Engineering Journal*, Vol. 5, No. 4, 2014, pp. 1129-1139.

[4] T. Stoeger, N, Battich, M. D. Herrmann, Y. Yakimovich and L. Pelkmans, "Computer vision for image-based transcriptomics", *Methods*, 2015.

[5] K. Wu and D. Zhang, "Robust tongue segmentation by fusing region-based and edge-based approaches", *Expert Systems with Applications*, Vol. 42, No. 21, 2015, pp. 8027-8038.

[6] L. Liu, N. Yang, J. Lan and J. Li, "Image segmentation based on gray stretch and threshold algorithm". *Optik-International Journal for Light and Electron Optics*, Vol. 126, No. 6, 2015, pp. 626-629.

[7] E. E. Kerre and M. Nachtegael, M, "Fuzzy techniques in image processing", Physica, Vol. 52, 2013.

[8] F. Russo, "Recent advances in fuzzy techniques for image enhancement", *Instrumentation and Measurement, IEEE Transactions on,* Vol. 47, No. 6, 1998, pp. 1428-1434.

[9] H. R. Tizhoosh, "Image thresholding using type II fuzzy sets", *Pattern recognition*, Vol. 38, No. 12, 2005, pp. 2363-2372.

[10] A. Z. Arifin, A. F. F. Heddyanna and H. Studiawan, "Ultrafuzziness optimization based on type II fuzzy sets for image thresholding", *Journal of ICT Research and Applications*, Vol. 4, No. 2, 2010, pp.79-94.

[11] J. Mohanalin, P. K. Kalra and N. Kumar, "A simple region growing technique for extraction of ROI from mammograms", *The IUP Journal of Systems Management*, Vol. 8, No. 4, 2010, pp. 56-62.

[12] C. V. Narayana, E. S. Reddy and M. S. Prasad, "Automatic Image Segmentation using Ultrafuzziness", *International Journal of Computer Applications*, Vol. 49, No. 12, 2012, pp. 6-13.

[13] S. Uyun, S. Hartati, A. Harjoko and L. Choridah, "Comparison between Automatic and Semiautomatic Thresholding Method for Mammographic Density Classification", *Advanced Materials Research,* Vol. 896, 2014, pp. 672-675.

[14] N. R. Pal and J. C. Bezdek, "Measures of fuzziness: a review and several new classes. *Fuzzy Sets", Neural Networks and Soft Computing, Van Nostrand Reinhold, New York*, 1994, pp. 194-212.

[15] M. Sezgin, "Survey over image thresholding techniques and quantitative performance evaluation". *Journal of Electronic imaging*, Vol. 13, No. 1, 2004, pp. 146-168.

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

*Table 1. Various Thresholding Algorithm In Mammogram Images*

| Images | Type II Fuzzy Sets | Type I Fuzzy Sets | Multi-Otsu Thresholding | Max Entropy | Moments | Proposed |
|---|---|---|---|---|---|---|
| Image 1 | 84,16 | 84,12 | 91,43 | 88,02 | 58,93 | 97,61 |
| Image 2 | 83,11 | 77,27 | 89,23 | 98,39 | 97,41 | 99,29 |
| Image 3 | 83,95 | 83,07 | 72,84 | 67,00 | 58,21 | 98,17 |
| Image 4 | 93,13 | 91,70 | 85,84 | 91,82 | 69,00 | 90,99 |
| Image 5 | 86,86 | 79,65 | 96,85 | 86,48 | 77,61 | 98,50 |
| Image 6 | 77,94 | 75,33 | 93,79 | 89,91 | 79,91 | 100,00 |
| Image 7 | 75,50 | 73,69 | 83,04 | 87,92 | 90,93 | 99,38 |
| Image 8 | 94,47 | 88,30 | 100,00 | 84,67 | 87,80 | 95,35 |
| Image 9 | 76,82 | 76,77 | 94,82 | 93,02 | 74,18 | 94,37 |
| Image 10 | 91,64 | 85,47 | 95,77 | 98,70 | 85,25 | 99,14 |
| Image 11 | 85,05 | 82,70 | 93,44 | 91,44 | 95,02 | 99,37 |
| Image 12 | 74,43 | 71,68 | 97,68 | 98,76 | 68,11 | 100,00 |
| Image 13 | 88,36 | 83,46 | 95,63 | 83,85 | 90,16 | 100,00 |
| $\mu$ | 84,26 | 81,02 | 91,56 | 89,23 | 79,36 | 97,86 |
| $s$ | 6,66 | 5,90 | 7,37 | 8,39 | 13,09 | 2,71 |