Automatic Image Segmentation using Ultrafuzziness

CH. V. Narayana
LBR College of Engineering
Mylavaram, India-521230

E. Sreenivasa Reddy
ANU College of Engineering
Guntur, India-522510

M. Seetharama Prasad
KL University, Vijayawada
India-522502

ABSTRACT
In this paper, an automatic histogram threshold approach based on a fuzzy measure is presented. This work is an improvement of an existing method. Using fuzzy logic concepts, the problems involved in finding the minimum/maximum of a entropy criterion function are avoided**.** Hamid R Tizhoosh defined a membership function to measure the image fuzziness, which makes the methodology totally supervised. We attempt to automate the process by taking an alternate approach. For low contrast images contrast enhancement is assumed. Experimental results demonstrate a quantitative improvement.

General Terms
Image segmentation, threshold,

Keywords
Type-I fuzzy, Type-II fuzzy, ultrafuzziness

1. INTRODUCTION
In many computer vision and image processing applications the fundamental task performed on image data is image segmentation, to process the foreground objects in order to explore the features. A well-known technique for image segmentation is thresholding, accuracy of segmentation is depends upon the process which is based on the gray level histogram. It is essential to find the threshold value to group into two well defined non-overlapping subsets. For an ideal image its histogram has a deep valley between two peaks. To locate the threshold valley region is the best place in bimodal histogram images because both peaks mostly representing the object and back ground pixels but it is not applicable for all types of images.

Image segmentation plays a vital role in Vision and Image processing applications. It is used widely in areas such as document image analysis, scene or map processing. Satellite imaging and material inspection in quality control tasks are examples of applications that employ image thresholding or segmentation to extract useful information from images. Medical image processing is another area that has extensively used image thresholding to help the experts to better interpret digital images for a more accurate diagnosis or to plan treatment.

Segmentation based on gray level histogram thresholding is a method to divide an image containing two regions ; object and background. In fact, applying this threshold to the whole image, pixels whose gray level is under this value are assigned to a region and the remainder to the other. Images are classified into unimodal, bimodal and multimodal depending on their histogram shapes. When the histogram doesn't exhibits a clear separation, ordinary thresholding techniques might perform poorly. Therefore there is a demand for a robust methodology to deal with all kinds of images as mentioned above. Fuzzy set theory provides better convergence when applied over non-fuzzy methods. This paper presents an automated method with fuzzy S-function and image ultrafuzziness as a fuzzy measure without an entropic criterion function.

In ideal cases the image histogram exhibits a deep valley between two peaks, each represents either an object or background and the threshold falls in the valley region. But some images will not express clear separation of the pixels as two peaks, where threshold computation is a difficult task. To address this problem several methods have been proposed in literature [1]-[5]. Otsu [6] proposed discriminant analysis to maximize the seperability of the resultant classes. An iterative selection method is proposed in reference [7]. J.Kittler and J.Illingworth's[8] proposed minimum error Thresholding method. Entropy based algorithms proposed by Kapur et al.[9] propose a method based on the previous work of pun[10] that first applied the concept of entropy to Thresholding. His methods concludes when the sum of the background and object entropies reaches its maximum, the image threshold is obtained. In Kapur et al.[9] Images which are corrupted with noise or irregular illumination produce multimodal histograms in which a 2D histogram does not guarantee the optimum threshold selection process, because no spatial correlation is considered. Entropy criterion function is applied on 3D GLSC histogram to optimize threshold by surpassing difficulties with 2D histogram [11,12]. This work is further enhanced by Seetharama Prasad et al.[13] with variable similarity measure producing improved GLSC Histogram. In reference [14] Type-2 fuzzy is used with GLSC histogram with human visual nonlinearity characteristics to identify the optimal similarity measure. The ordinary Thresholding techniques perform poorly where, non-uniform illumination corrupts object characteristics and inherent Image vagueness is present. Fuzzy based Image Thresholding methods are introduced in literature to overcome this problem. Fuzzy set theory[15] is used in these methods to handle grayness ambiguity or image vagueness during the process of threshold selection. Several segmentation algorithms based on fuzzy sets are found in the literature [16]-[20]. *Fuzzy clustering* ideas for thresholding are in focus[21]-[23], used fuzzy memberships based on pixels distance from each class's mean to define which class a pixel belongs to and subsequently define the threshold as the cross over point of membership functions. Several segmentation algorithms based on fuzzy sets are found in the literature based on Fuzzy measure, which is a measure of vagueness in the image used in many segmentation algorithms[25][27], the gray level intensity value is selected to be the optimum threshold at which the fuzzy index is minimized. Hamid R. Tizhoosh[26] introduced a new fuzzy measure called ultrafuzziness and also a new a membership function Haung and Wang [28] assigns a membership degree to each pixel in the image, and the image is considered as a fuzzy set and the membership distribution explains each pixel belongs to either objet set or background set in the misclassification region of the histogram. Hamid R. Tizhoosh[29] introduced a new thresholding methodology based on oppositional fuzzy. Research performed by

Tizhoosh et al.[30], the authors introduced opposition-based fuzzy thresholding, called OFT henceforward, and combine the concepts of fuzzy memberships and opposition- based computing to extract some local information of the image that leads to selecting a threshold value.
The remainder of this paper is organized as follows: section 2 describes the existing method; section 3 describes the proposed method, section 4 shows comparative results and improved yielding of our method and section 5 ends up with conclusion.

2. EXISTING METHOD

In the existing method Tizhoosh[31] introduced a new fuzzy membership function along a new fuzzy measure called ultrafuzziness using type II fuzzy sets to compute a threshold for the image segmentation.

2.1 Tizhoosh's Fuzzy membership function

To measure the image fuzziness Hamid R.Tizhoosh[26] defined a new membership degree function as shown in Equation (1) which comprises of three unknown quantities α ,β and T must be estimated from the image statistics.

$$\mu(g) = \begin{cases} 0 & g \le g_{min} \text{ or } g \ge g_{max} \\ L(g) = \left\{\frac{g-g_{min}}{T-g_{min}}\right\}^{\alpha} & g_{min} \le g \le T \\ R(g) = \left\{\frac{g_{max}-g}{g_{min}-T}\right\}^{\beta} & T \le g \le g_{max} \end{cases}$$

(1)

In this experiment we have considered α ,β both values are equal to 2.

2.2. Type I fuzzy sets

The most common measure of fuzziness is the linear index of fuzziness. For a MxN image subset A⊆ X with gray levels g ⊆ [0,L-1], the linear index of fuzziness can be estimated as follows

$$\gamma_1(\mathrm{A}) = \frac{2}{MN}\sum_{g=0}^{L-1} h(g) \times min\,[\mu_A(g), 1-\mu_A(g)] \qquad (2)$$

Where μ_A (g) is obtained from Equation (1). So the optimal threshold can be obtained though maximizing the linear index of fuzziness criterion function that is given by

$$t^* = \text{Arg max} \{\gamma(\mathrm{A}: \mathrm{T})\}, 0 \le \mathrm{T} \le \mathrm{L}\text{-}1 \qquad (3)$$

2.2 Type II fuzzy sets

Definition. A tupe II fuzzy set Ã is defined by type II membership function X $\mu_{\tilde{A}}(x,u)$, where x ∈ X and

u ∈ J_x ⊆ [0,1]

Ã can be expressed in the notation of fuzzy set as

$$\tilde{A} = \{((x, u), \mu_{\tilde{A}}(x,u)) | \subseteq {}_{x}\in X, {}_{u} \in J_x \subseteq [0,1]\},$$

in which $0 \le \mu_{\tilde{A}}(x,u) \le 1$

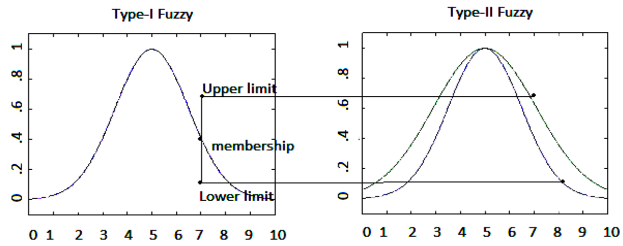


Fig 1: A possible way to construct type II fuzzy sets. The interval between lower/left and upper/right membership values (bounded region) will capture the footprint of uncertainty

A type II fuzzy set can be defined from type I fuzzy set and assign upper and lower membership degrees to each element to construct the foot print of uncertainty as shown in Figure 1. a more suitable definition for a type II fuzzy set can be given as follows:

$$\tilde{A} = \{X, \boldsymbol{\mu_U} \le (\boldsymbol{x}), \boldsymbol{\mu_L}(\boldsymbol{x}) |\, {}_x\in X, \quad \boldsymbol{\mu_L}(\boldsymbol{x}) \le \mu(\boldsymbol{x}) \le \boldsymbol{\mu_U}(\boldsymbol{x}), \mu \in [0,1] \qquad (4)$$

The upper and lower membership degrees $\boldsymbol{\mu_U}$ and μ_L of initial membership function μ can be defined by means of linguistic hedges like dilation and concentration:

$$\boldsymbol{\mu_U}(\boldsymbol{x}) = [\mu(\boldsymbol{x})]^{\mathbf{0.5}},$$

$$\boldsymbol{\mu_L}(\boldsymbol{x}) = [\mu(\boldsymbol{x})]^{\mathbf{2}},$$

Hence, the upper and lower membership values can be defined as follows:

$$\boldsymbol{\mu_U}(\boldsymbol{x}) = [\mu(\boldsymbol{x})]^{\frac{1}{\Delta}},$$

$$\boldsymbol{\mu_L}(\boldsymbol{x}) = [\mu(\boldsymbol{x})]^{\Delta},$$

Where Δ ∈ (1,∞) but Δ>2 is usually not meaningful for image data.

2.3.Tizhoosh Ultrafuzziness

The degrees of membership is defined without any uncertainty as type I fuzzy sets, automatically the ultrafuzziness also tend to zero. When individual membership values can be indicated as an interval, the amount of ultrafuzziness would increase. The maximum ultrafuzziness is one when the information of membership degree values are totally ignored. For a type II fuzzy set, the ultrafuzziness is defined as γ for a M x N image subset Ã⊆ X with gray levels g ⊆ [0,L-1], histogram h(g) and membership function $\mu_{\tilde{A}}(g)$ can be defined as follows: $\gamma(\tilde{A}) = \frac{1}{MN}\sum_{g=0}^{L-1} h(g) X\, [\mu_U(g) - \mu_L(g)]$

(5)

where

$$\mu_U(g) = [\mu(g)]^{\frac{1}{\Delta}},$$

$$\mu_L(g) = [\mu(g)]^{\Delta}, \ \Delta \in (1,2)$$

3. PROPOSED METHOD

The existing method has several drawbacks in constructing the fuzzy membership degree function. The three unknown quantities α ,β and T are to be estimated from the image statistical parameters of the image histogram. Since they vary from one image to another it becomes difficult to automate the entire process of image thresholding. We considered the standard S-function to compute membership degree of the fuzziness of the given image. Seetharama Prasad et al. [32] derived most convincing method to compute initial fuzzy seed subset when S-function described in Figure 2, is used.

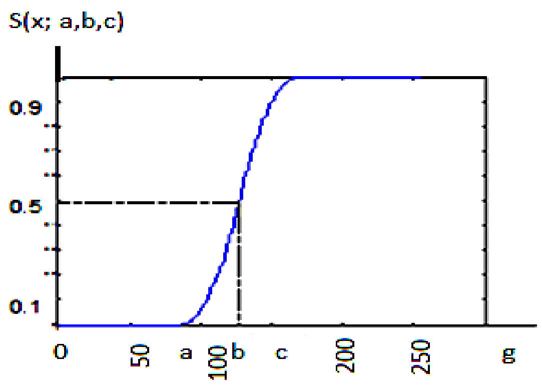


Fig 2: Shape of the S-function

The S- function is used for modeling the membership degrees as shown in Figure 2. For object pixels

μ_O (x) = S (x; a, b, c)

$$= \begin{cases} 0 & x < a \\ 2\left\{\frac{x-a}{c-a}\right\}^2 & a \le x \le b \\ 1-2\left\{\frac{x-c}{c-a}\right\}^2 & b \le x \le c \\ 1 & x \ge c \end{cases} \qquad (6)$$

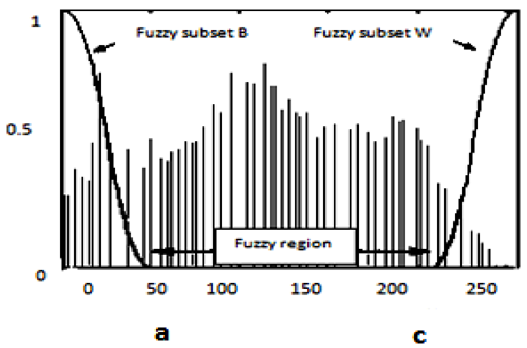


Fig: 3 Multimodal image histogram and the characteristic functions for the seed subsets.

From reference [31] initial fuzzy seed subset values a, b and c are computed. Let $x(i, j)$ be the gray level intensity of image at (i,j). I={ x(i, j)|I ∈ [1,Q], j ∈ [1,R]} is an image of size Q x R, i.e. N. The gray level set {0,1,2,…..255}. The mean(μ) and standard deviation(σ) are calculated as follows

$$\mu = \frac{1}{N}\sum_{i=1}^{n} x_i \times h(i) \qquad (7)$$

$$\sigma = \sqrt{\frac{1}{N}\sum_{i=1}^{n}(x_i - \mu)^2} \qquad (8)$$

From Equations (7) and (8) fuzzy seed set values a, b and c as shown in Figure 3, are estimated as

$$b = \mu \qquad (9)$$

$$a = \mu - \sigma \qquad (10)$$

$$c = \mu + \sigma \qquad (11)$$

3.2 Thresholding with fuzzy sets of type II using s_function

The general algorithm for image thresholding based on type II fuzzy sets and measure of Ultrafuzziness can be formulated as follows:

1. Select S-membership function
2. Initial fuzzy seed sub set values of S-function are computed from Equations (8), (9) & (10)
3. Calculate image histogram
4. Initialize the position of the membership function
5. Shift the membership function along the gray-level range
6. Calculate in each position the amount of ultrafuzziness from Equation(5)
7. Find out the position g_{opt} with maximum ultrafuzziness
8. Threshold the image with $t^* = g_{opt}$

Kaufmann[24] introduced an index of fuzziness first to measure the vagueness of a fuzzy set. He also established four conditions that every measure of fuzziness should satisfy. This fuzzy measure, ultrafuzziness is also satisfying his four conditions. so the optimal threshold can be obtained though minimizing the ultrafuzziness criterion function that is given by

$$t^* = \text{Arg } \min \{ \gamma(\tilde{A}: T)\}, 0 \le T \le L-1 \qquad (12)$$

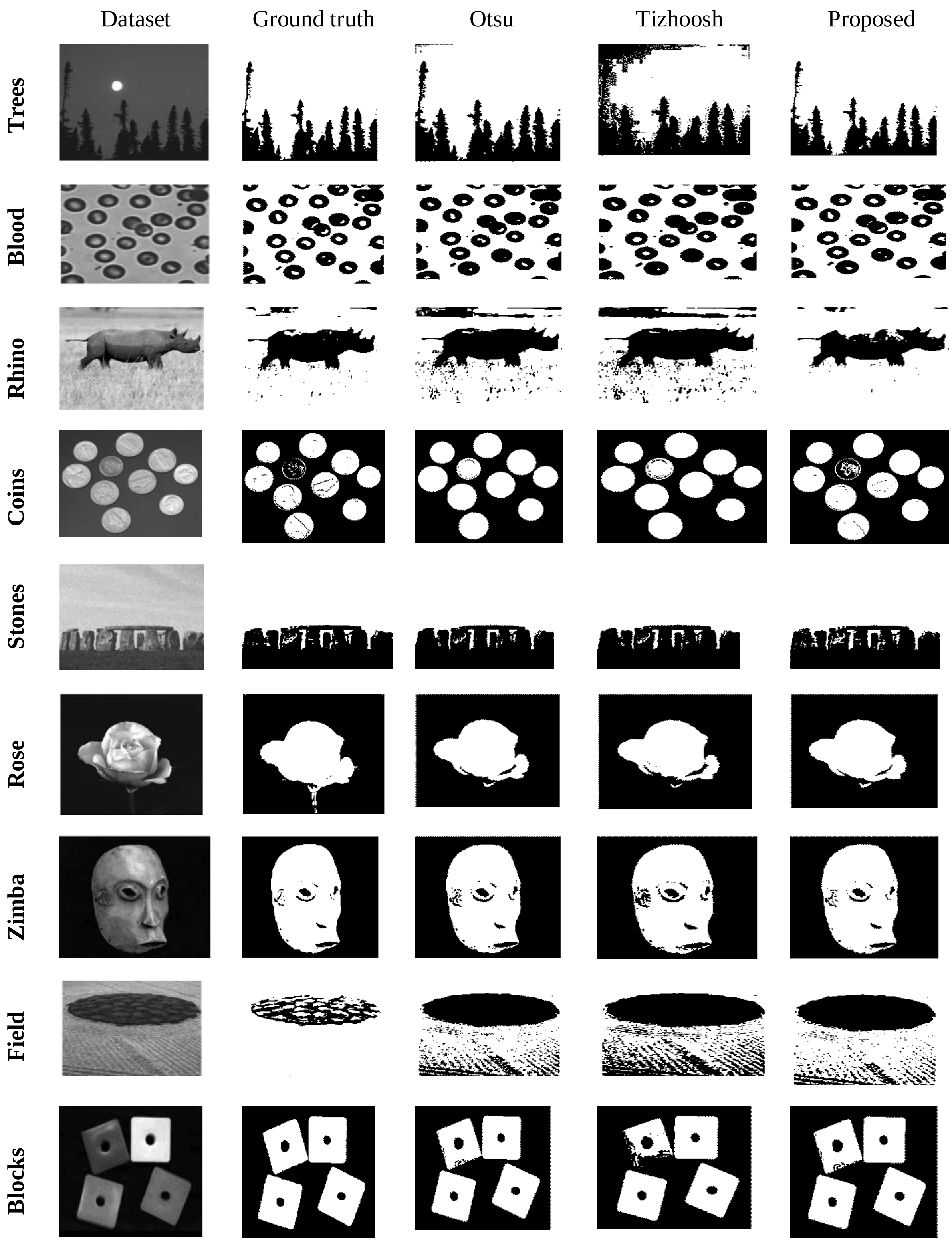
4. RESULTS AND DISCUSSIONS

To illustrate the performance of the proposed methodology we consider 15 images as an image set having similar and dissimilar gray level histogram characteristics, varying from uni-model to multimodal. gold standard groundtruth images are generated manually to measure a parameter efficiency (η) based on misclassification error[5] and Jaccard Index[32].

4.1 Misclassification Error

$$\text{Misclassification Error } (\boldsymbol{\eta}) = \frac{|\,\mathbf{IMG_O} \cap \mathbf{IMG_T}\,|}{|\,\mathbf{IMG_O}\,|} \text{ X } 100 \quad (13)$$

Where, IMG_O, IMG_T are gold standard image and resultant image respectively and |*| is the Cartesian Number of the set gives number of pixels. This η would be 0 for absolutely dissimilar and 100 for exactly similar image as result. Figure 4 shows original image set and their possible gold standard threshold image set. From the experiments for each image we obtain misclassification error values against its corresponding ground truth image from different methods including OTSU's, Tizhoosh and Proposed in Table 1.


Dataset
Ground truth
Otsu
Tizhoosh
Proposed
Trees
Blood
Rhino
Coins
Stones
Rose
Zimba
Field
Blocks

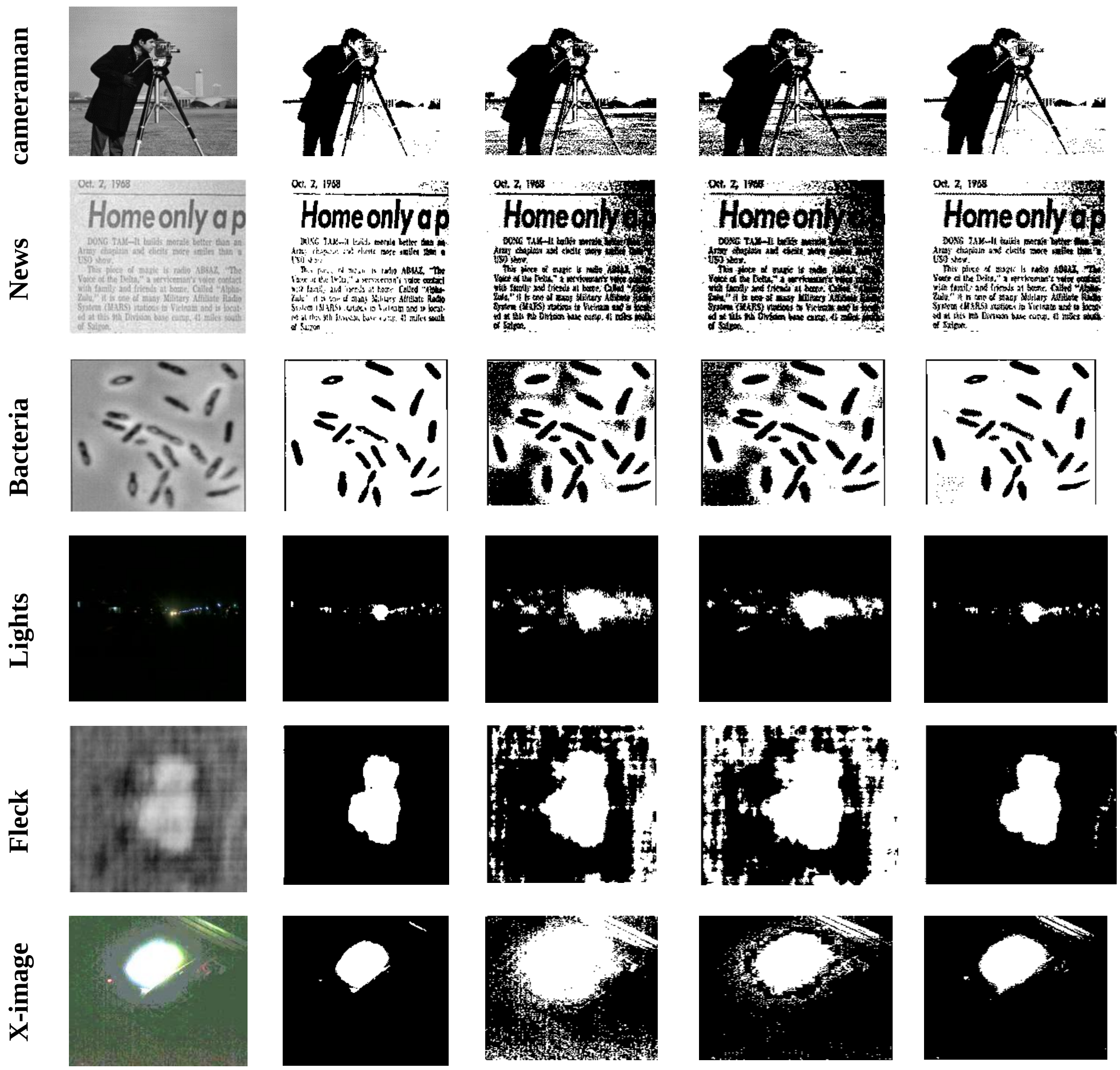


Fig 4: (From left to right) Data set, ground truth images and corresponding results for the three algorithms, Otsu, Tizhoosh and Proposed

Table 1: Efficiency using Misclassification Error (η %)

Sl.no	Image	Otsu	Tizhoosh	Proposed
1	Trees	97.07	84.63	99.46
2	Blood	96.95	96.27	98.53
3	Rhino	92.92	89.85	96.97
4	Coins	96.17	96.49	98.61
5	Stones	99.42	99.49	99.50
6	Rose	98.55	97.78	98.84
7	Zimba	99.44	98.26	99.71
8	Field	77.49	68.78	79.68
9	Blocks	98.95	96.44	98.95
10	Cameraman	90.28	85.96	99.68
11	News	82.74	77.39	91.75
12	Bacteria	76.81	80.68	98.81
13	Lights	92.84	94.91	99.49
14	Fleck	77.44	62.82	99.03
15	X-image	66.86	88.63	95.70

MEAN (μ)	89.59	87.89	96.98
STD (σ)	10.55	11.28	5.22

From the experiments for each image we obtain η % for Otsu, Tizhoosh and proposed methods as shown in TABLE 1. These values are compared with assumed gold standard image data. Figure 5 confirms a variation in above said methods on histogram range for image set considered against Otsu method. Efficiency (η) is calculated for each technique on image set with Equation (13). A mean (μ) and standard deviation (σ) are calculated on efficiency in order to show the effectiveness of the proposed and other methods as in TABLE 1. A mean 96.98 and standard deviation 5.22 is obtained from the proposed method which confirms the qualitative improvement over the existing methods.

4.2 Jaccard Index

The another similarity measure is the Jaccard Index [32] known as Jaccard similarity coefficient, very popular and frequently used as similarity indices for binary data. The area of overlap A_j is calculated between the thresholded binary image B_j and its corresponding gold standard image G_j as shown in Equation (14).

$$\text{Jaccard Index } (A_i) = \frac{|B_i \cap G_i|}{|B_i \cup G_i|} \times 100 \qquad (14)$$

Table 2: Efficiency using Jaccard Index (%)

Sl.no	Image	Otsu	Tizhoosh	Proposed
1	Trees	94.30	73.36	98.92
2	Blood	94.08	92.81	97.10
3	Rhino	86.78	81.56	94.12
4	Coins	92.62	93.21	97.27
5	Stones	98.88	98.99	99.00
6	Rose	97.14	95.65	97.70
7	Zimba	98.88	96.58	99.42
8	Field	63.25	52.41	66.29
9	Blocks	97.93	93.13	97.93
10	Cameraman	82.28	75.38	99.36
11	News	70.56	63.11	84.75
12	Bacteria	62.35	67.62	97.65
13	Lights	86.64	90.31	98.98
14	Fleck	63.18	45.79	98.09
15	X-image	50.21	79.58	91.75
	MEAN (μ)	82.60	79.97	94.55
	STD (σ)	16.33	16.77	8.74

If the thresholded object and corresponding gold standard image G_j (associated ground truth image) are exactly identical then the measure is 100 and the measure 0 represents they are totally disjoint, but the higher measure indicates more similarity. Table 2 represents the effectiveness of the proposed method, and Figure 6 shows the superiority of the proposed method against Otsu and Tizhoosh methods. From table 2 with Jaccard index, the proposed method has highest average performance of 94.55% with the lowest standard deviation 8.74% . In contrast Otsu algorithm with 82.60% average performance and 16.33% standard deviation and Tizhoosh method average performance of 79.97% and 16.77% standard deviation. Therefore the proposed method is clearly showing best performance against the existing methods.

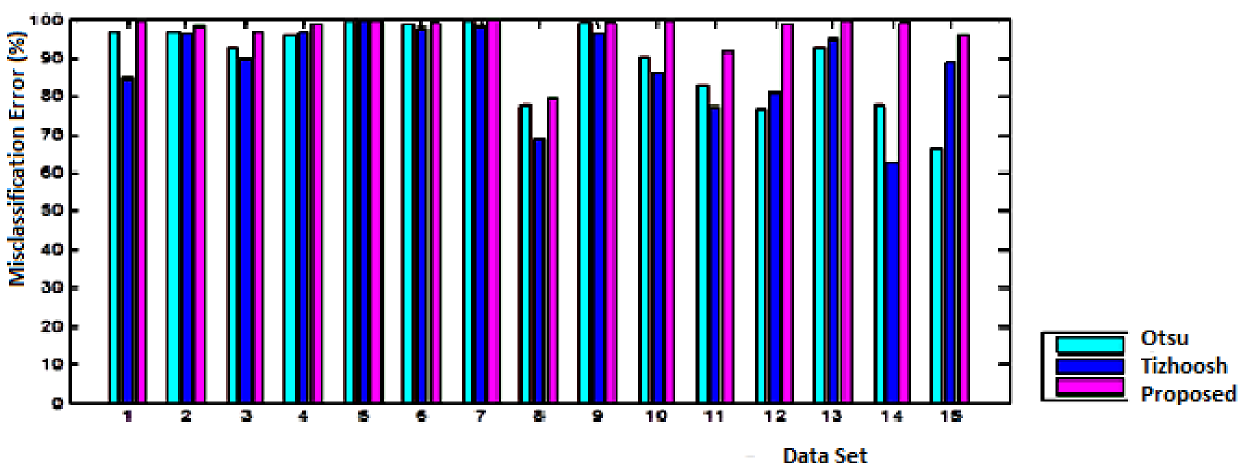


Fig: 5 Efficiency comparison of the proposed method against Otsu and Tizhoosh using Misclassification error

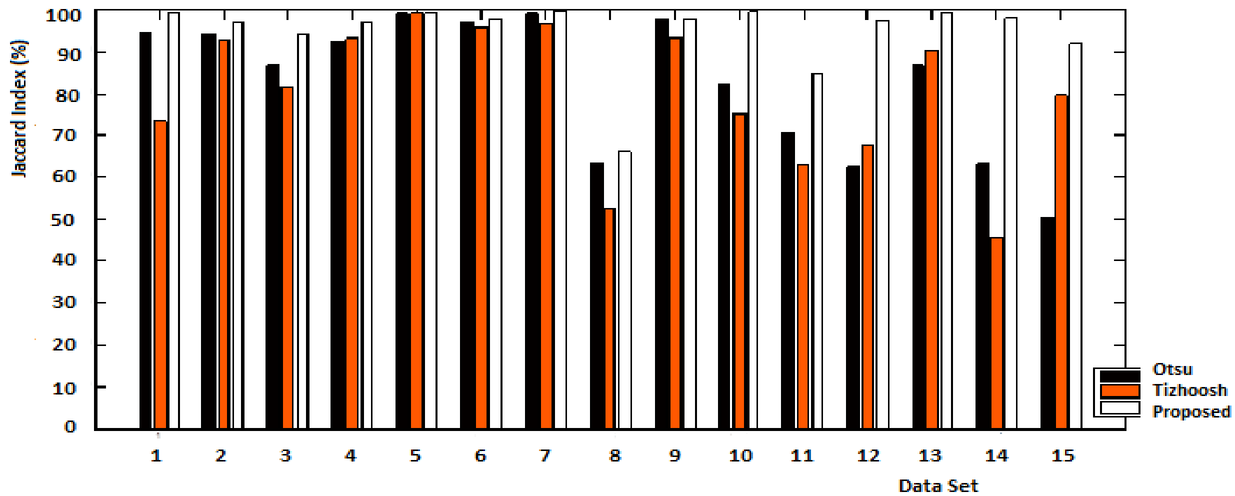


Fig: 6 Efficiency comparison of the proposed method against Otsu and Tizhoosh using Jaccard Index

5. CONCLUSION

In this paper an automated segmentation approach based on Tizhoosh fuzzy measure called ultrafuzziness is presented. Tizhoosh [29] in his work, introduced a new fuzzy membership function with many parameters which is not very easy to converge. Therefore the existing procedure has a scope to be automated, In our approach we tried with fuzzy S-membership function in the place of Tizhoosh membership function and the process is totally automated with the help of Seetharama Prasad et al.[31]. However, this method can be further improved and tested against other fuzzy membership functions available or a still new suitable membership function can be derived. Efficiency of threshold selection is demonstrated with experimental results. We assume a reasonable contrast enhancement for low contrast images. Performance evolution is carried out with the help of two popular approaches; Misclassification error and Jaccard Index on the proposed work.

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8.EDITOR'S PROFILE

CH.Venakata Narayana, did his M.Tech(CSE) from JNT U pursuing his Ph.D in DIP from AN Univesity, Guntur. He h research papers in various international journals. He is Pres Associate Professor in LBRCE, Mylavaram .

Dr. Sreenivas Reddy received the B.Tech(ECE) from Nagarjuna University, India in 1988, M.S. degree from Birla Institute of Technology and Scince, India in 1997, M.Tech (CS) from Visveswaraiah Technological University, India in 2000 and Ph.D in Computer science from Acharya Nagarjuna Univeristy, India in 2008. Currently he is guiding many Ph.D scholars for several universities. He is the senior member of IEEE and presented many papers in international conferences and several journal papers. His research interest includes image processing, biometrics and pattern recognition.

Dr. M. Seetharama Prasad, presently working as a Professor at KL university, did his B.E(cse) from University of Mysore in 1989, M.E(cse) from Vinayaka Missions University in 2007, and Ph.D in Computer Science and Engineering from Chandra Mohan Jha University in 2012, India. He has published ten research papers in various