Image Segmentation Based On FUZZY GLSC Histogram With Dynamic Similarity Discrimination Factor

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ABSTRACT :- Image pressing applications performes image segmentation as pre-processing technique to extract the features for next stage. The application performance depends on image segmentation, to process the foreground or background objects. The image segmentation plays a vital role in computer vision and image processing applications. Inspite of having many thresholding techniques in literature they have their own limitations. This paper proposes a new method of thresholding using Gray Level Spatial Correlation (GLSC) histogram with a dynamic similarity discrimination factor(ζ) and Fuzzy logic in deciding the threshold using Shannon's entropy. The similarity discrimination factor(ζ) is made dynamic by considering the absolute difference between the global and local mean of the image. Calculating the threshold in the fuzzyfied region makes the segmentation process the most time efficient than the existing methods. Experimental results proove better efficiency η than the existing methods. The technique out performs in case of low contrast images.

Keywords :- Entropy, Fuzzyfication, Fuzzyfied image, GLSC histogram, threshold.

1. INTRODUCTION

Image threshold is a simple and popular technique for image segmentation used in image processing applications to separate foreground or background of an image. For a well defined image its histogram has a deep valley between two peaks. The valley region is the best place to locate the threshold in bimodal histogram images because most of the time peaks represents the object and background pixels but it is not applicable for all types of images. Many threshold methods are lagging in generosity of their application found in litereature[1-3], still it is an area where the research is alive. Otsu proposed discrimination analysis to find threshold, failing in low contrast images [4].Based on statistical measures like mean, variance, standard deviation Otsu derived threshold. Shannon introduced information theory based on the concept of entropy [5].Pun used this entropy concept to derive threshold [6]. Kapur et.al. improved the work of Pun [7]. This is extended to Renyi's entropy [8-9] and Tsalli's entropy [10-11]. Yang Xiao et.al. improved this work by constructing 3D Gray Level Spatial Correlation (GLSC) histogram [12] by considering local properties of image at constant similarity measure 4 which overcomes the time complexity of 2D histogram approaches [13]. The usage of 3D histogram instead of 2D will result better threshold value, Gray Level Spatial Correlation (GLSC) Histogram along with entropic techniques is the recent advancement in this context In this paper we propose an image segmentation technique based on GLSC histogram with dynamic similarity discrimination factor (ζ) by considering local and global characteristics, to improve the method proposed by Yang Xiao. The parent version algorithm using a constant 4 as the similarity measure to construct a 3D histogram on a 3×3 window image, does not suits for all types of images. Using Fuzzy technique to extract fuzzyfied region[14] in image and calculating threshold using Shannon's entropy[15] in this region itself makes the proposed image segmentation technique very time efficient. The redistribution of missing probability amount in floating precisions is made to improve the performance of proposed method. The parameter efficiency η based on misclassification error between segmented image and ground truth image is more than the existing methods. The remainder of this paper is organized as follows: section 2 explains existing method; section 3 explains proposed method; section 4 illustrates comparative results of proposed, existing methods and parameter efficiency of proposed method over existing method; section 5 ends up with conclusion.

2. EXISTING METHOD

The 2D histogram will produce same threshold for different images having same no of pixels in each intensity level with different pixel distribution. The Gray Level Spatial Correlation (GLSC) histogram which takes in to account the spatial correlation of the pixel with its neighborhood differentiates the images with same frequency but different placements. To overcome this problem a 3D Gray Level Spatial Correlation (GLSC) histogram with a constant similarity measure 4 is constructed. Let f(x, y) be the gray value of the pixel located at the point (x, y) in a digital image F= { f(x, y) | x∈{1,2………..Q}, y∈{1,2………R} of size Q× R. For the sake of convenience, we denote the set of all gray levels {0, 1, 2…255} as G. The GLSC histogram is computed as follows. The figure 2.1 illustrates GLSC histogram with a constant similarity measure (ζ).

$$g(x,y) = \sum_{i=-\frac{N-1}{2}}^{\frac{N-1}{2}} \sum_{j=-\frac{N-1}{2}}^{\frac{N-1}{2}} \left(|f(x+i,y+j) - f(x,j)| \leq \zeta \right) \text{------1}$$

where

$$(|f(x+i,y+j)-f(x,j)| \leq \zeta) = \begin{matrix} 1 \text{ if } \ |f(x+i,y+j) - f(x,y)| \leq \zeta \\ 0 \ \text{ if } |f(x+i,y+j) - f(x,y) > \zeta \end{matrix} \quad \text{--- 2}$$

While computing the g(x, y), disregarding the N rows from the top and bottom and N the columns from the sides. The pixels gray value, f(x, y), and g(x, y) are used to construct the GLSC histogram using h(k,m)=Prob(f(x,y)=k and g(x,y)=m) ----------------3

Where, p is gray level correlation probability computed for all pixels with intensity $k \in G$ and $m \in \{1,2,.........N \times N\}$ and histogram is normalized [12]. As Yang Xiao said the existing method gives its best results with similarity measure ζ = 4 and N=3.Shannon's entropy is used in estimation of threshold value on GLSC histogram instead of 2D histogram with a defined weight for the taken map N=3 and corresponding correlation values from the equations 4 and 5.

$$(t, N)=H_o(t, N) + H_b(t, N) \quad \text{--------------------------4}$$

$$t=\text{Arg max}\ (t, N) \quad \text{--------------------------5}$$

where (t, N) is the entropic criterion function , $H_o(t, N)$ and $H_b(t, N)$ are object and background entropies respectively. The normalized histogram is approximated by using the formula

$$\hat{h}(k, m)=\frac{\text{no of pixels with gray value k and m pixels of similar gray value in } N \times N \text{ neighborhood}}{\text{no of pixels in the image}} \quad \text{-------------------------------6}$$

3. PROPOSED METHOD

The existing method proposed by Yang Xiao gives best results at similarity measure 4 but it is not generous to all types of images since it considers only local properties of image. The Gray Level Spatial Correlation (GLSC) histogram which is constructed with a constant similarity measure 4 can be extended by making the similarity measure as a dynamic value. We propose a Gray Level Spatial Correlation (GLSC) histogram with a dynamic similarity discrimination factor ζ which takes into account the local and global properties of image. The combined probability of object and background must be unity, but due to floating precisions some amount is missing in both the probabilities. The missing probability is compensated by equally distributing across the probability function p(k, m). We propose a Fuzzy technique to extract the fuzzyfied region in the GLSC histogram of the image. The co-ordinates of fuzzified region is obtained from the proposed GLSC histogram. Using these co-ordinates the fuzzy functions (s, pi, z) extract the fuzzyfied region from the GLSC histogram of the image. We use the Shannon's entropy in the estimation of the threshold value. The entropic criterion function is calculated at each and every pixel in the extracted misclassified region or fuzzyfied region of GLSC histogram. The point at which the entropic criterion function becomes maximum, we choose that point as threshold value. By restricting the threshold calculation to the extracted fuzzyfied region itself, the time complexity to calculate the threshold value is reduced. By introducing the fuzzy technique, the proposed method becomes very time efficient. The process involved in the proposed method and the corresponding intermediate results at each stage is illustrated as shown in Fig. 3.1.

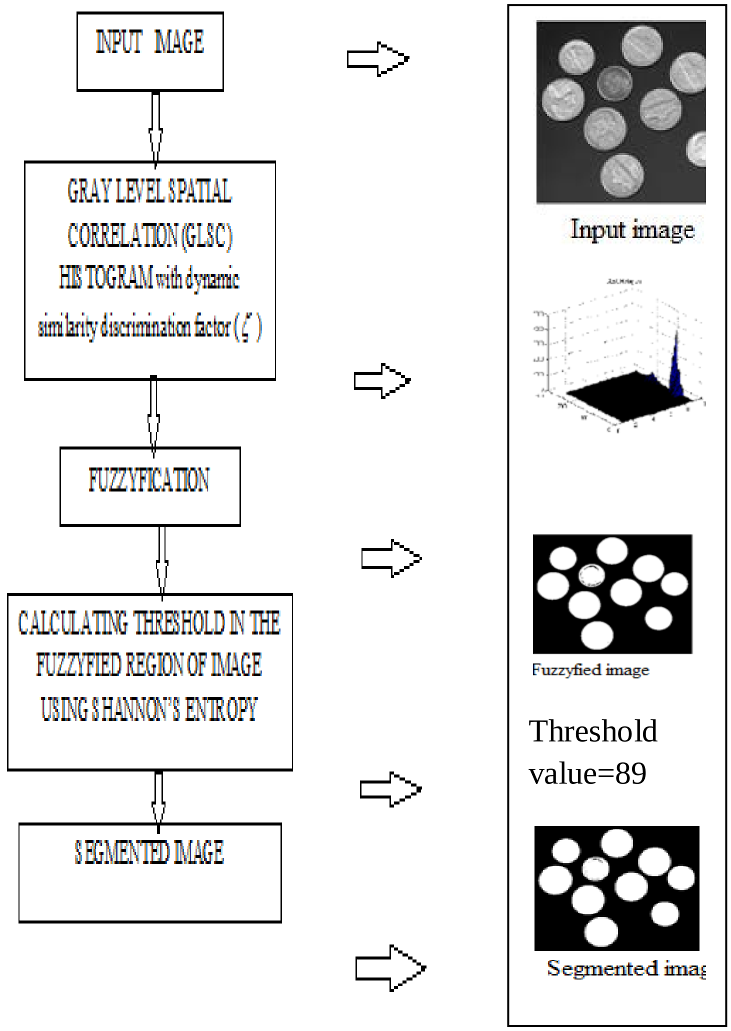


Fig. 3.1 Flowchart of the proposed image segmentation tecnique

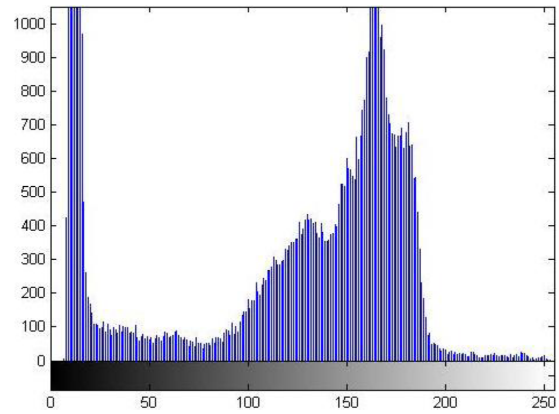
3.1. GLSC histogram with dynamic simi larity discriminattion factor ζ

We construct Gray Level Spatial Correlation (GLSC) histogram with dynamic similarity discrimination factor ζ which takes in to account the local and global properties of image.In the existing method Yang Xiao constructed it at constant similarity measyre 4.The dynamic similarity discrimination factor ζ is calculated for every N $\times$ N map of image.The similarity discrimination factor ζ is made dynamic by considering the absolute difference between the local mean of the considered N $\times$N window and global mean of the image. As the considered local window changes, the local mean changes, consequently the absolute difference between local and global mean changes.

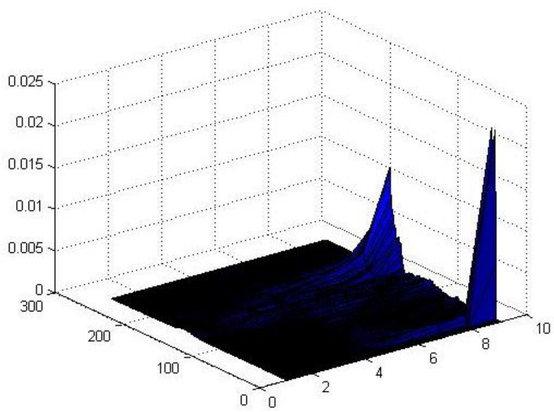
$$\zeta = |M_g - M_l| \quad \text{-------------------------7}$$

The time complexity for calculation of ζ is less when compared other statistical measures like variance, co-variance and standard deviation. The proposed Gray Level Spatial correlation (GLSC) histogram with new ζ is contructed with equations 1 and 2.Fig. 3.2.a shows 'coins.tif' image for which the 2D ,3D GLSC with constant similarity measure 4 and 3D GLSC histogram with dynamic similarity discrimination factor ζ is shown in Fig. 3.2.b, 3.2.c, 3.2.d respectively. The 2D histogram represent two peaks with object and background, the ame is represented in GLSC ,in GLSC histogram with dynamic similarity measure it is represented by considering the local and global properties of image Which is used to extract fuzzyfied region of image and helps Shannon's entropy to attain optimal threshold.

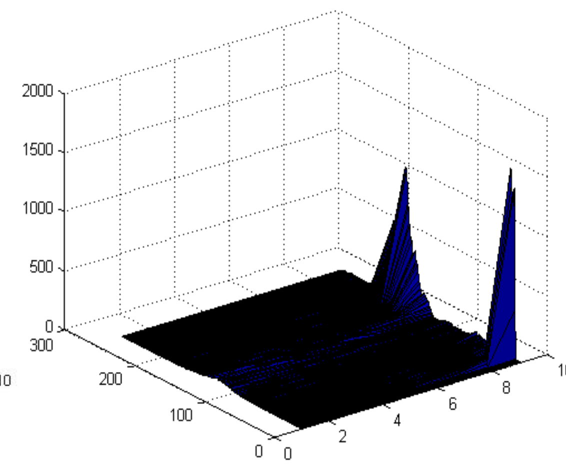
a cameraman



b Conventional 2D histogram



c GLSC histogram with 4 ζ



d GLSC histogram with dynamic ζ

Fig. 3.2 coins image, 2D histogram ,GLSC and GLSC with dynamic similarity discrimination factor ζ

3.2. Extracting the fuzzyfied region of histogram using Fuzzy technique

Histograms of images with two distinct regions are formed by two peaks separated by a deep valley called bimodal histograms as seen in Fig. 2.2.b. In such cases, the threshold value must be located on the valley region. When the image histogram does not exhibit a clear separation, ordinary thresholding techniques might perform poorly. The Fuzzy technique provide a new tool to deal with this sort of histograms as shown in Fig. 2.3.1.

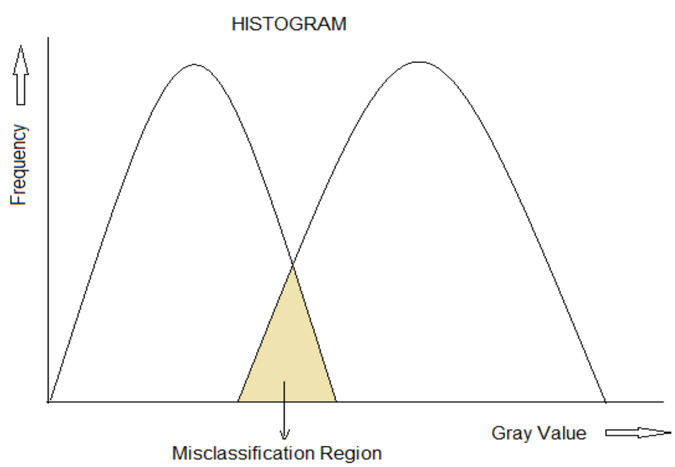


Fig. 3.2.1 Multimodal histogram

The fuzzy s, pi, z functions are used to ectract the fuzzy zone of the image histogram and the respective zone is analized for the fuzzyfication process with the help of GLSC Histogram and the seed values are obtained from the proposed Histogram. The fuzzy functions are derived as

F(X)=

$$\begin{array}{lll} 0 & \text{if} & X<A \\ (X-A/C-A)^{2} & \text{if} & A<X<C \quad \text{--------------------8} \\ 1 & \text{if} & X>C \end{array}$$

The equation for the z plot is given by

F(X)=

$$\begin{array}{lll} 1 & \text{if} & X<A \\ 1-(X-A/C-A)^{2} & \text{if} & B<X<C \quad \text{-------------------9} \\ 0 & \text{if} & X>C \end{array}$$

The pi plot is the combination of s and z plots.The co-ordinates required for these functions are obatained from the costructed GLSC histogram with dyanmic similarity discrimination factor (ζ).The seed values are obtained as

B = µ(weighted GLSC Histogram) ------------------10

A = B - σ(GLSC Histogram) ------------------11

C = B + σ (GLSC Histogram) ------------------12

4. RESULTS AND DISCUSSIONS

To illustrate the performance of the proposed image segmentation technique we consider 19 images as an image Database, varying from uni-modal to multimodal and the corresponding gold standard ground truth images are generated manually to measure a parameter efficiency η based on misclassification error using Equation(13)

$$\eta = \frac{|IMG0 \cap IMG1|}{|IMG0|} \times 100\ \% \text{----------------13}$$

Where IMG_O and IMG_T are ground truth image and segmented images respectively. This efficiency η would be 0 for imperfect matching of images and 100 for perfectly matched images. Fig. 4.1 shows original image set and possible ground truth image set. Efficiency η is calculated for each technique on image to dig the performance analysis more detailed the image set is divided into three different groups from the histogram response as uni-model, bimodal and multi-model. The performance plots are shown in performance plots in fig-(). In each category The proposed method outperforming the existing algorithms. The sample output images are shown in fig (-). The mean efficiency confirms quantitative improvement over existing methods.

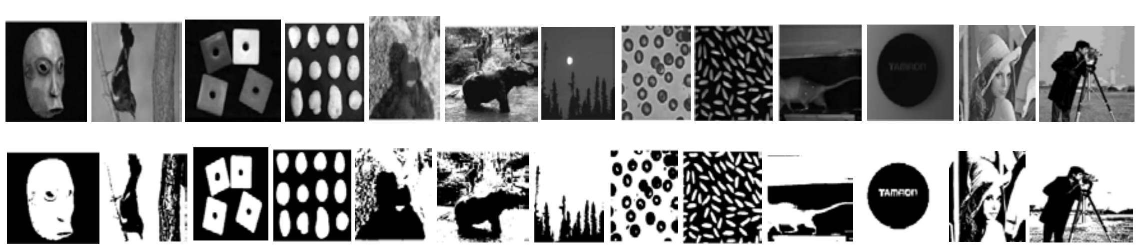


Fig. 4.1 Original image Data set and possible ground truth images

TABLE 1: Performance comparision of Uni model Images

S.no	Image	Proposed Method	Improved GLSC	GLSCH	Otsu	Entropy
1.00	Scull	100.00	98.69	61.67	96.50	44.04
12.00	Roof	96.12	89.91	72.88	80.52	77.48
13.00	Roof heads	96.16	99.24	58.38	99.33	12.41
14.00	Sheat	94.20	92.16	81.25	89.21	28.88

TABLE 2: Performance comparision of Bi model Images

S.no	Image	Proposed Method	Improved GLSC	GLSCH	Otsu	Entropy
4.00	Potatoes	99.69	99.52	77.32	97.39	88.70
7.00	Trees	98.75	99.60	68.14	28.29	33.27
8.00	Blood cells	99.00	99.82	84.21	97.90	86.85
16.00	Anshu	96.58	97.67	60.29	96.92	71.04
17.00	Wall flower	99.03	96.40	75.55	95.56	64.84
19.00	Coins.	99.61	99.56	70.80	97.86	81.18

TABLE 3: Performance comparision of Multi model Images

S.no	Image	Proposed Method	Improved GLSC	GLSCH	Otsu	Entropy
2.00	Bird	97.21	92.23	76.36	96.13	84.85
3.00	Blocks	98.43	99.12	52.79	72.00	86.80
5.00	Shadow	94.21	97.85	94.62	98.71	98.29
6.00	Forest	97.33	93.62	74.62	90.23	100.00
9.00	Rice	98.42	98.62	61.81	96.67	81.23
10.00	Animal	96.14	97.92	78.50	52.29	84.24
11.00	Emblem	98.66	94.22	72.51	66.46	89.47
15.00	Lena	92.92	92.00	94.06	91.44	95.02
18.00	Camera man	96.21	93.55	91.68	91.57	84.69

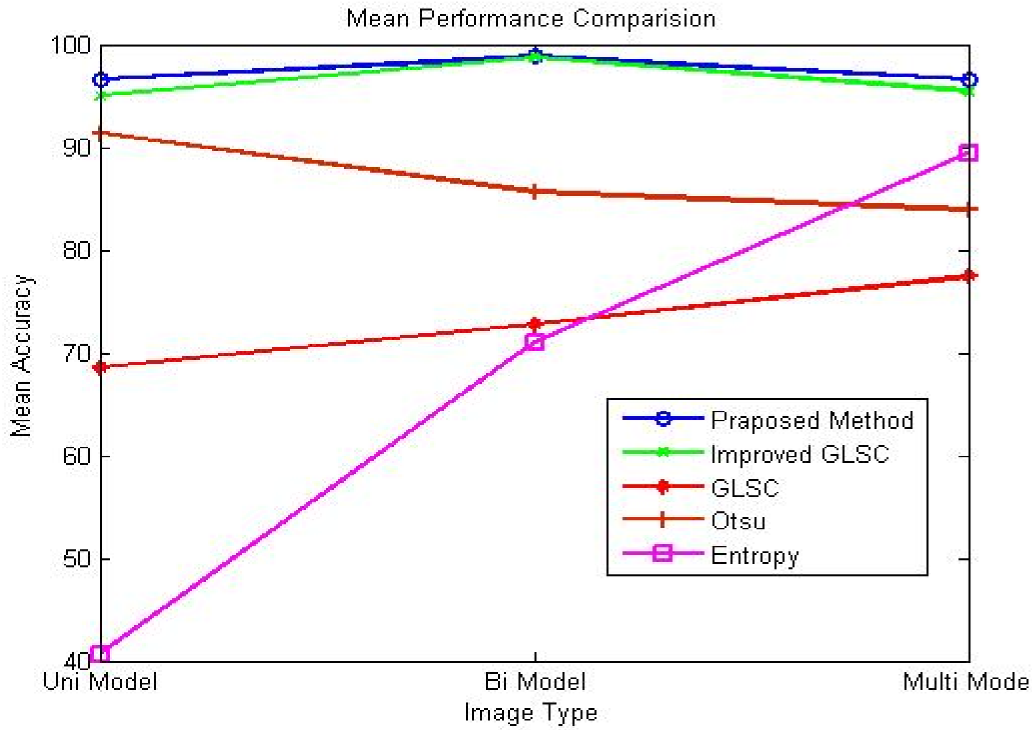


Fig 4.1: Mean Performance Comparison

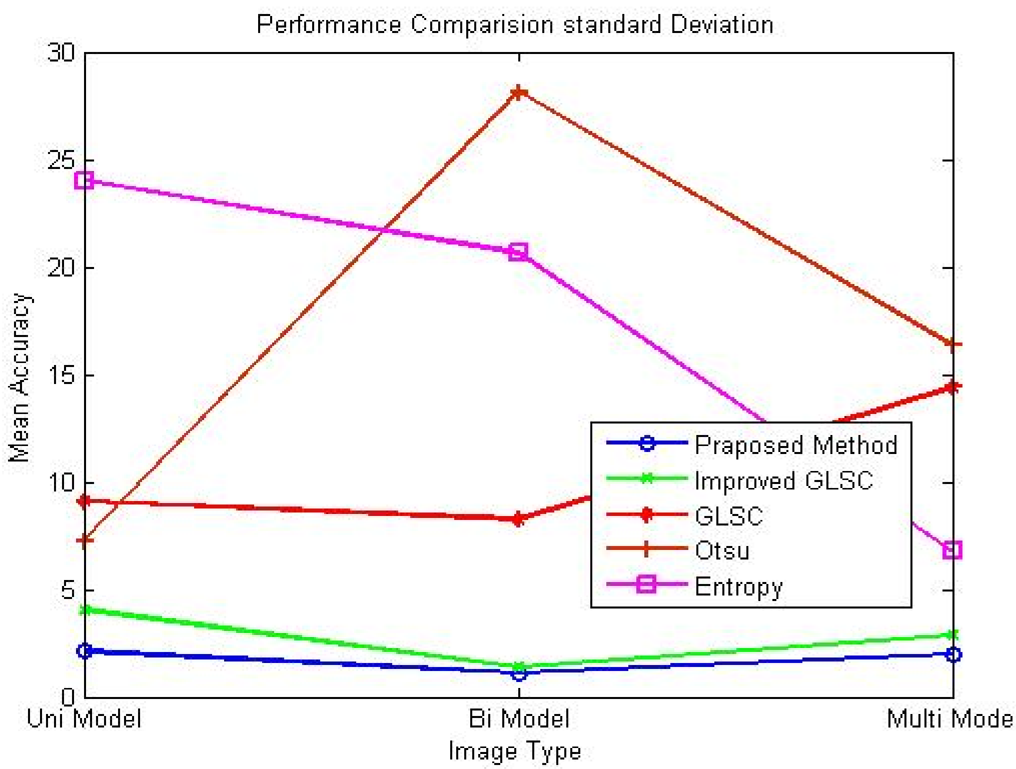
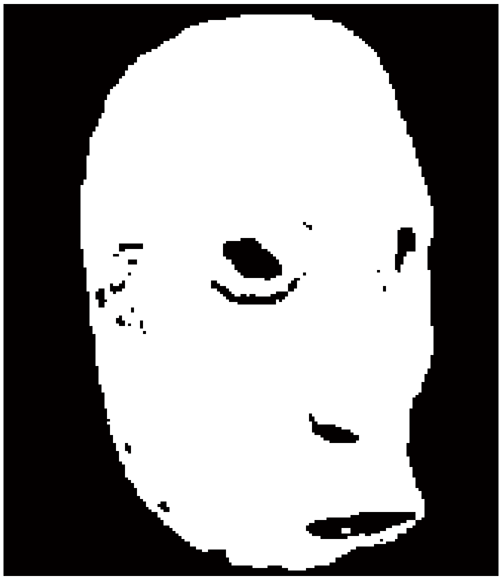
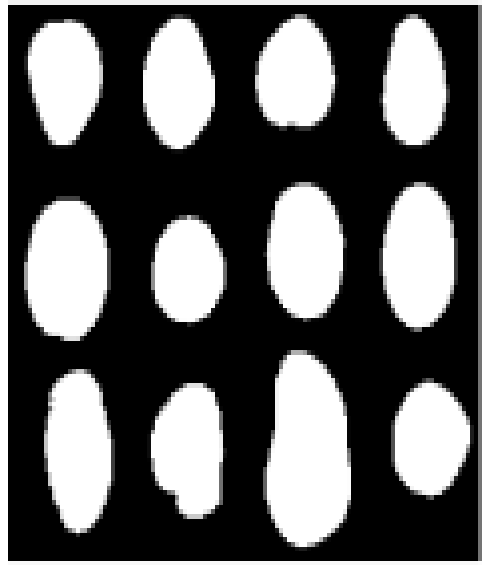


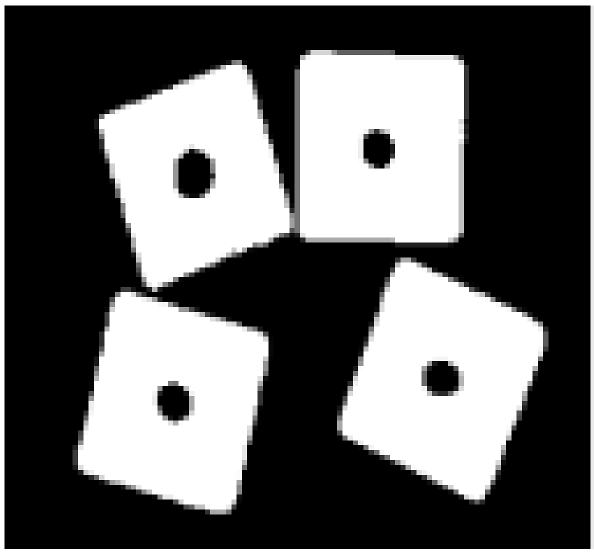
Fig 4.2: Performance Comparison Standard deviation



a. Uni-model Segmented image



b. Bi model segmented Image



c. Multi model segmented Image

fig 4.3: Sample Output images of Proposed method

5. CONCLUSION

In this paper a segmentation technique based on GLSC histogram with dynamic similarity discrimination factor (ζ) using fuzzy technique is proposed. The proposed Technique is suitable for much range of applications due to generalization of discrimination factor and its computational complexity is reduced by introducing fuzzy techniques into the logic to fix the misclassification region. Proposed work differs with Yang Xiao's in construction of GLSC histogram and using it to find Fuzzy seed values to locate fuzzy region of image histogram. The GLSC histogram considers the spatial correlation of pixels in computing the correlation matrix g(x,y). The existing method with constant ζ suffers under the conditions where different background brightness intensities effecting the object characteristics. The use of Fuzzy technique makes the proposed segmentation process time efficient. Performance evolution is carried out with the help of misclassification error on proposed method, improved GLSC, GLSCH, Otsu's and Kapur's entropy technique. Evaluation is categorized into three groups based on histogram models the proposed technique outperforming existing techniques in all three categories with reduces computational efficiency.

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