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Quantitative Evaluation and Analysis of Image Segmentation Techniques

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Abstract- This paper focuses on quantitative evaluation and analysis of image segmentation techniques. Image segmentation techniques are being widely used and choosing suitable image segmentation technique is one of the key factors for getting better results. In this paper image segmentation techniques have been evaluated in two categories which are image thresholding techniques and clustering based image segmentation techniques. Various techniques under these categories have been analyzed and compared. Some well-known metrics have been used for evaluation and comparison of performance of these techniques.

Keywords- Image segmentation techniques, Image thresholding techniques, Clustering techniques, OTSU, FCM, K-means, K-medoid, Gath-Geva, Gustafson-Kessel, Local thresholding techniques, Dunn's Index.

I. Introduction

Image processing is a very wide area which includes image acquisition, image pre-processing, image segmentation, pattern recognition and feature classification. Out of these, image segmentation is an important area which helps in analysis of images and to get useful information out of image keeping constraints in mind like memory requirements, object of interest, and post-processing techniques to be used. In the image segmentation process interested regions are extracted from the image. There exist a large number of segmentation techniques, so often it becomes a problem to make a decision about the suitability of segmentation technique i.e. which technique to use according to our requirement. It becomes a tedious task to judge which method will provide better results. Since the comparative analysis of some image segmentation techniques has been carried out in the paper so that it can benefit others to make decision about the choice of image segmentation technique required. Analysis has been done on many techniques under two categories that are image thresholding techniques and clustering based image segmentation techniques. Performance of these techniques is measured with some well known parameters using standard Berkley database.

The approach used in this paper has been organized in following manner, section 2 describes different type of image segmentation techniques which are analyzed in this paper, section 3 describes metrics used for performance evaluation, and section 4 shows experimental results which include both qualitative results as well as quantitative results, section 5 gives conclusion.

II. Image Segmentation Techniques

Two major categories compared in this paper are image thresholding techniques and clustering based image segmentation techniques. All the techniques compared under these categories are described as follows.

A. Image thresholding techniques

Thresholding techniques divide an image into two classes i.e. foreground and background on the basis of a threshold value. Thresholding techniques avaluated in this paper are described as follows.

OTSU Thresholding uses the method of minimizing the weighted sum of within-class variances of the foreground and background pixels in image to get the optimum threshold value. As the within class variances are minimized, between-class are automatically maximized [1]. Optimal threshold in OTSU is given by eq. 1.

$$T_{opt} = argmax\left[\frac{P(T).(1-P(T)).\left(m_f(T)-m_b(T)\right)^2}{P(T)\sigma_f^2(T)+[1-P(T)]\sigma_b^2(T)}\right] \quad (1)$$

An improved image segmentation algorithm based on OTSU by Huang, Yu and Zhu [2] was presented in 2012. In this method the selection range for the appropriate threshold value is narrowed. It was done by using two threshold values. One lower threshold value was calculated and one upper threshold value. Optimal threshold value is finally selected from the gray values lying between the range of lower threshold value and the upper threshold value. The gray level value lying in this range, which gives the minimum variance ratio i.e. the ratio of intra-class variance to the inter-class variance, is selected as the optimal threshold value. Lower threshold T_1 and upper threshold value T_2 are given by eq. 2.

$$T_1 = \sum_{i=0}^{T_0}\frac{i*p_i}{P_{w1}} \quad \text{And} \quad T_2 = \sum_{i=T_0+1}^{L-1}\frac{i*p_i}{P_{w2}} \quad (2)$$

Where t_0 is the mean gray value of image on basis of which initially pixels are divided in two classes W_1 and W_2, p_i is the probability of pixels with gray value i and P_{w1} and P_{w2} are the sum of probabilities of pixels in class W_1 and W_2 respectively. Variance for class W_1 and W_2 are given by eq. 3.

$$\sigma_{w1}^2 = \sum_{i=0}^{T} \frac{(i-\mu_{w1})^2 * p_i}{P_{w1}} \quad \text{And} \quad \sigma_{w2}^2 = \sum_{i=T+1}^{L-1} \frac{(i-\mu_{w2})^2 * p_i}{P_{w2}} \tag{3}$$

Where u_{w1} and u_{w2} are the mean of classes W_1 and W_2 respectively. Intra class and Inter class variance are given eq. 4.

$$\sigma_w^2 = \sigma_{w1}^2 + \sigma_{w2}^2 \quad \text{And} \quad \sigma_i^2 = P_{w1}P_{w2}(\mu_{w1} - \mu_{w2})^2 \tag{4}$$

Now gray level value between range *[T1, T2*] which gives minimum variance ratio (Intra-class to inter-class) is taken as optimal threshold value.

An image thresholding method based on standard deviation by Li and Liu [3] was presented in 2009. In this method thresholding using standard deviation was presented. In this Li and Liu defined an objective function using standard deviation of two classes created by any gray level value and minimizing the objective function to get the optimal threshold value.

Standard deviation for two classes C_1 and C_2 divided by some gray value was given by eq. 5

$$\sigma_1 = \left(\frac{1}{N_1}\sum_{i=0}^{k}(i-\mu_1)^2 n_i\right)^{\frac{1}{2}}, \quad \text{And} \quad \sigma_2 = \left(\frac{1}{N_2}\sum_{i=k+1}^{L-1}(i-\mu_2)^2 n_i\right)^{\frac{1}{2}} \tag{5}$$

where N_1 and N_2 are the number of pixels in C_1 and C_2 , u_1 and u_2 are the means of gray values in C_1 and C_2 respectively, n_i is the number of pixels with gray level intensity i.

The objective function defined by Li and Liu is given by eq. 6.

$$OBJ = \sigma_1^2 + \sigma_2^2 - \sigma_1\sigma_1 \tag{6}$$

This objective function is calculated for all the gray levels from 0 to 255 and the gray level giving minimum value of objective function is taken as the optimal threshold value.

Niblack's Loacal Thresholding [4] uses a local variance based method for calculating the local threshold. In Niblack local thresholding method threshold is calculated based on some local mean and standard deviation with in a window of size *w*x*w.* So the threshold T(x,y) for pixel (x,y) for window of size *w* x *w* is given by eq. (7).

$$T(x,y) = m(x,y) + k\delta(x,y) \tag{7}$$

Where *m(x,y)* and $\delta(x,y)$ are the mean and standard deviation in local window. *k* is the bias. As the value of mean and standard deviation changes according to the contrast in the local neighbourhood of the pixel, accordingly the value of threshold keeps changing.

Bernsen's local thresholding [5] used local gray scale range technique. In this type of techniques mean value between the maximum and minimum intensity values in window is taken as threshold according to the given logic. In Bernsen's technique local threshold value $T(x,y)$ at pixel *(x,y)* calculated within a window of size $w\times w$ as in eq. (8) :

$$T(x,y) = 0.5\,(I_{\max(i,j)} + I_{\min(i,j)}) \tag{8}$$

Where, $I_{\min(i,j)}$ and $I_{\max(i,j)}$ represents the minimum and maximum gray level value within the window with a given contrast defined in eq. (9).

$$C\,(i,j) = I_{\max(i,j)} - I_{\min(i,j)} \geq 15 \tag{9}$$

Threshold is set at a midrange value by taking the mean of minimum and maximum gray values in the given window of size $w\times w$. If the contrast *C(i,j)* is below a certain threshold i.e. 15 then that neighbourhood is said to be in the same class foreground or background according to the threshold *T(x,y).* No bias is used to control threshold value.

B. Clustering based image segmentation techniques

Clustering techniques segment image by dividing all the pixels of the image into desired number of clusters. Clustering techniques are mainly divided in two categories: Hard Clustering (also known as hard partitioning) methods and Soft Clustering (also known as fuzzy partitioning) methods.

In Hard clustering K-means and K-medoid are discussed.

K-means clustering algorithm was given by MacQueen [6]. It is an iterative algorithm which initially chooses some random cluster centers and finds the points closest to these center points, as a member to these clusters. This procedure is repeated until the points stop changing their cluster. K-means algorithm is shown below [7].

Algorithm: K-means

Set a value of k.
Randomize k cluster center values.
While (an object changes its cluster)
For every object
Find cluster center which gives minimum distance.
Assign object to that cluster.
End for
For every cluster
Adjust a cluster center as mean of every object in the cluster.
End for
End while

Partitioning Around Medoid (PAM)/K-medoid method proposed by Kaufman and Rousseeuw [8]. It uses a similar partitioning method as of k-means. This method chooses some objects out of all given objects as the medoid points (cluster center points) instead to random points as cluster centers as in k-means. K-medoid is more robust to noise as compared to K-means. Algorithm is shown below[7].

Algorithm: K-medoid
Set value of k.
Choose k objects randomly from all objects in dataset as medoids.
While (medoids of every cluster change position)
For every object
Find medoids which gives the minimum distance.
Assign that object into that cluster with minimum distance.
End for
For every cluster
Adjust medoid by setting the object which has the minimum average distance between itself and other objects in the same cluster as new medoids.
End for
End while

In Soft clustering Fuzzy c-means (FCM), Gath-Geva and Gustafson-Kessel techniques are discussed.

Fuzzy c-means (FCM) was proposed by Dunn [9] and later on it was modified by Bezdek [10]. FCM assigns pixels to each class by means of fuzzy membership function. Let's suppose $X = (x_1, x_2, x_3 \ldots x_N)$ denotes an image with N pixels to be categorized into C clusters. FCM is the iterative minimization of the following objection function J (eq. 10).

$$J = \sum_{j=1}^{N}\sum_{i=1}^{C} \mu_{ij}^{m} \left\|x_j - v_i\right\|^2 \tag{10}$$

Where u_{ij} is the membership of pixel x_j in *ith* cluster, v_i is the *ith* cluster center, m is the fuzzifier that controls the fuzziness of resulting partitions and lies between $1 < m \leq \infty$ and $\|.\|$ is a norm metric. Usually Euclidean distance between pixel x_j and the center of *ith* cluster v_i, is used as norm metric as in [11] and [12].The membership function and cluster centers are updated repetitively according to formulas provided by Dunn and Bezdek. The cluster centers can either be initialized randomly or by an approximation method.

Gath-Geva [13] is based on fuzzy maximum likelihood estimates (FMLE). The fuzzy maximum likelihood estimates (FMLE) clustering uses a distance norm based on FMLE given by Bezdek and Dunn [14]. Distance norm is given in eq. (11).

$$D_{ik}\,(\mathrm{x}_k\,,\mathrm{v}_i) = \frac{\sqrt{det\,(F_{wi})}}{\alpha_i}\exp\left(\frac{1}{2}\left(\mathrm{x}_k - \mathrm{v}_i^{(l)}\right)^T F_{wi}^{-1}\left(\mathrm{x}_k - \mathrm{v}_i^{(l)}\right)\right) \tag{11}$$

Distance norm defined in Gath-Geva contains an exponential term so it decreases faster as compared to inner-product norm. Gath and Geva [13] said that FMLE clustering algorithm has the ability to detect different type of shapes, sizes and densities. However, algorithm is comparatively less robust in sense that it requires a good initialization as it converges to the nearest local optimum value due to the exponential distance norm.

Gustafson-Kessel algorithm [15] modified the standard FCM algorithm. It used an adaptive distance norm to detect clusters of different shapes created by given data set. In this each cluster has its own separate norm-inducing matrix A_i. So the inner-product norm is calculated as (eq. 12).

$$D_{ikA}^2 = (x_k - v_i)^T A_i (x_k - v_i),\ 1 \le i \le c,\ 1 \le k \le N \quad (12)$$

Matrices A_i work as optimization variable in c-mean functional so that each cluster can adapt distance norm according to structure of data. The Gustafson-Kessel algorithm [15] associates each cluster with both a point and a matrix, respectively representing center of the cluster and its covariance. Unlike the original fuzzy c-means which make the implicit hypothesis that clusters are of spherical shape, the Gustafson-Kessel algorithm is not subject to this constraint and can identify ellipsoidal clusters. The cluster centre is computed as a weighted mean of the data, the weights depending on the considered algorithm, as detailed in the following. The covariance matrix is defined as a fuzzy equivalent of classic covariance. Cluster parameter updating step is alternated with the update of the weighting coefficient until a convergence criterion is met.

III. Metrics for Performance Measurement

TRUE POSITIVE RATE: In context of our work True Positive (TPOS) contains those parts of image that are present in the ground truth as well as in the result image. True Positive Rate is the probability of correct identification of foreground pixels. It is given by the eq. (13).

$$TPOS_{rate} = \frac{TPOS}{TPOS + FNEG} \quad (13)$$

FALSE POSITIVE RATE: In context of our work False Positive (FPOS) contains those parts of the image that are present in the result image but not present in the ground truth image. False positive rate is the probability of incorrect identification of background pixel as foreground pixels. It is given by eq. (14).

$$FPOS_{rate} = 1 - TNEG_{rate} \quad (14)$$

TRUE NEGATIVE RATE: In context of this work True Negative (TNEG) contains those parts of the image that are not present in the result image as well as in the ground truth image. True negative rate is the probability of correctly rejecting wrong pixels. It is given by eq. (15)

$$TNEG_{rate} = \frac{TNEG}{TNEG + FPOS} \quad (15)$$

FALSE NEGATIVE RATE: In context of this work False Negative (FNEG) contains those parts of the image that are not present in the result image but are present in the ground truth image. False negative rate is the probability of incorrectly rejecting the right pixels. It is given by eq. (16).

$$FNEG_{rate} = 1 - TPOS_{rate} \quad (16)$$

ROC curve: It is the graph plotted between True positive rate and false positive rate. More points plotted nearer to the Y-axis and as farther from X-axis is considered as better results. For clustering such parameters have been taken which shows how much well-separated and well-shaped clusters these techniques make for given type of data.

Partition Coefficient (PC): it measures the amount of "overlapping" between clusters. It is defined by Bezdek [10] as given in eq. (17).

$$PC(c) = \frac{1}{N}\sum_{i=1}^{c}\sum_{j=1}^{N}(\mu_{ij})^2 \quad (17)$$

where μ_{ij} is the membership of data point *j* in cluster *i*. The optimal number of cluster is at the maximum value.

Classification Entropy (CE): it measures the fuzziness of the cluster partition only, which is similar to the Partition Coefficient as given in eq. (18).

$$CE(c) = -\frac{1}{N}\sum_{i=1}^{c}\sum_{j=1}^{N}\mu_{ij}\,log(\pi_{ij}) \quad (18)$$

Dunn's Index[9]: this index is originally proposed to use at the identification of well separated and compact clusters. Therefore the output of the clustering is again calculated as it was a hard partition algorithm as given in eq. (19).

$$DI(c) = min_{i\in c}\left\{min_{i\in c, i\neq j}\left\{\frac{min_{x\in c_i, y\in c_j} d(x,y)}{max_{k\in c}\{max_{x,y\in c}\, d(x,y)\}}\right\}\right\} \quad (19)$$

IV. Experimental Results

The Berkeley database has been used to testing all techniques and collecting results. From Berkley database [16] a set of 20 images has been used for testing. All experiments were carried out using MATLAB®, Version 7.11.0 (R2010b) with Image Processing toolboxes.

Results of thresholding techniques on swan image are shown in figure 1.

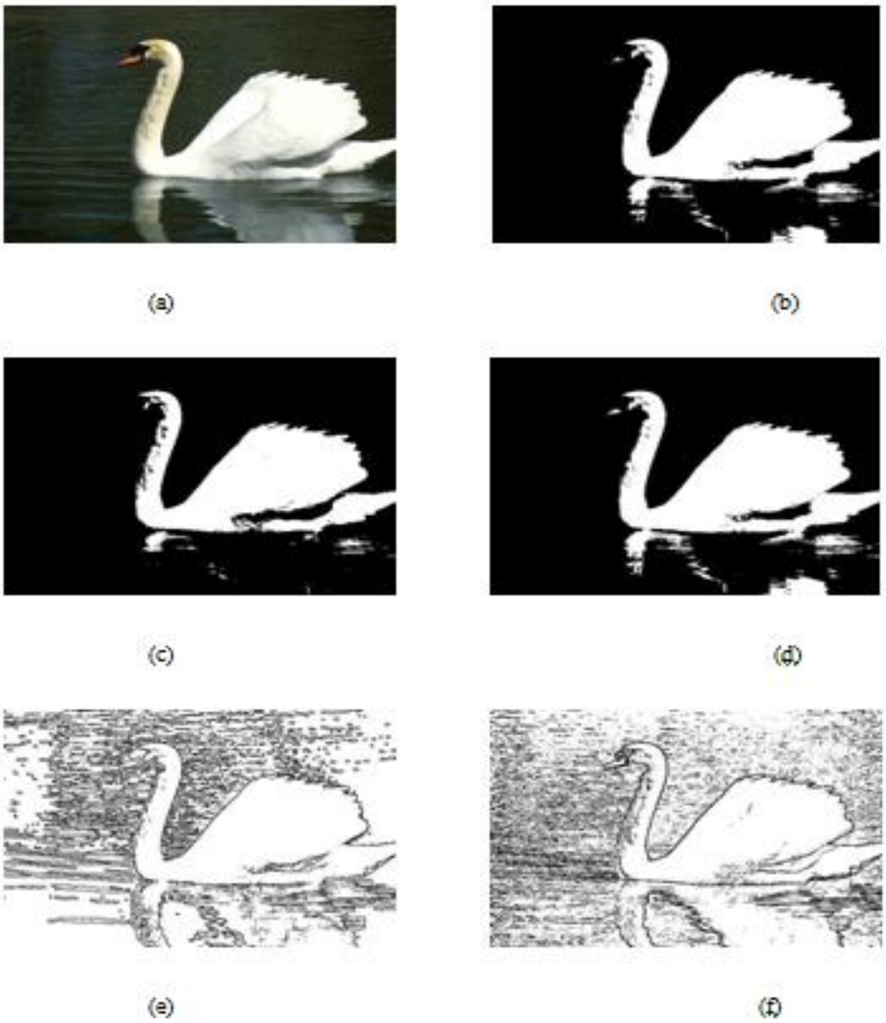


Figure 1 : Output of thresholding techniques: (a) Original image (b) Otsu (c) Threshoding based on standard deviation (d) Improved thresholding based on Otsu (e) Bernsen (f) Niblack

Quantitative results for thresholding techniques are shown in figure 2 and figure 3.

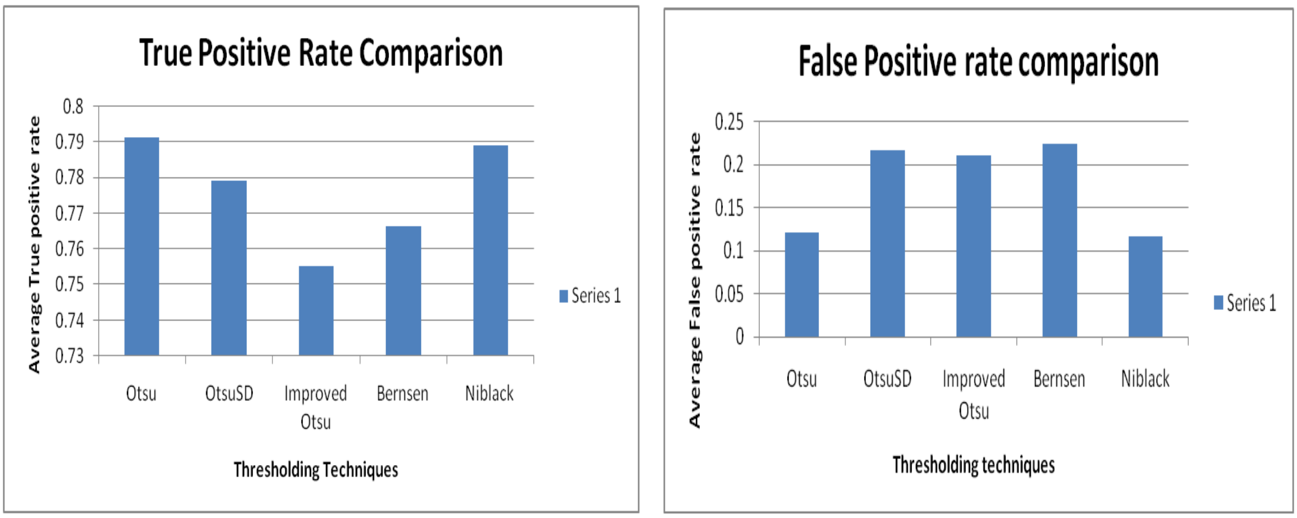


Figure 2: True positive rates comparison and false positive rate comparison for thresholding techniques.

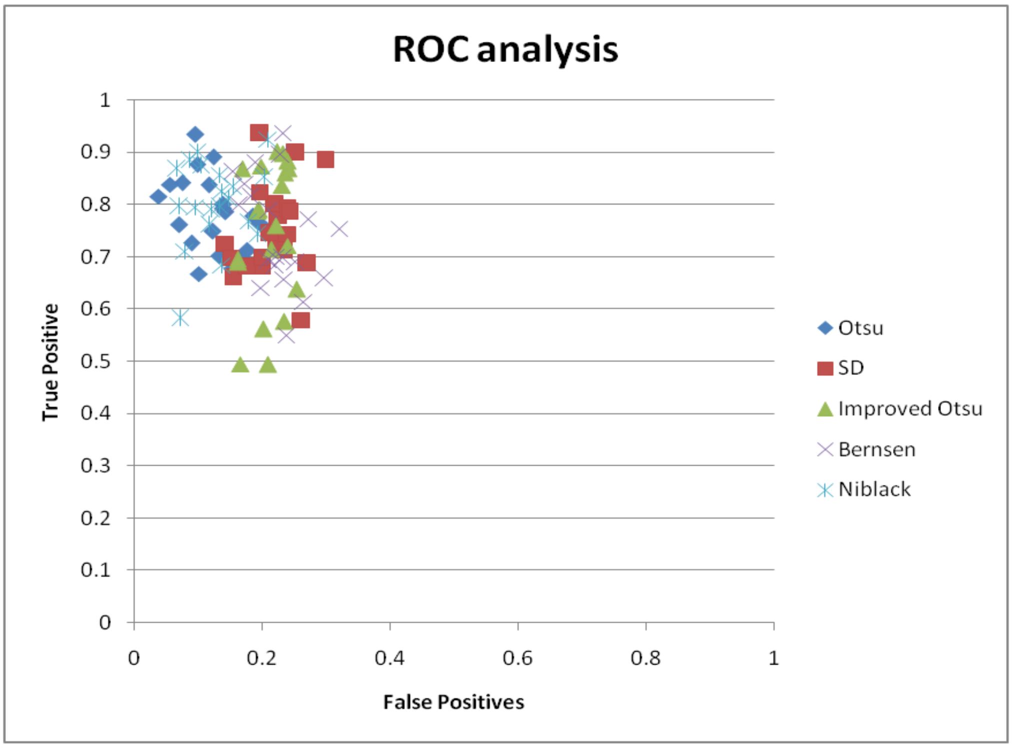


Figure 3: ROC analysis for thresholding techniques.

K-means and K-medoid are hard partitioning techniques and FCM, Gath-Geva and Gustafson-Kessel techniques are fuzzy partitioning techniques. As the basic methodology, approach and concept of both categories are different so these two categories are compared separately. Partition Coefficient and Classification entropy parameters are used for analysis of soft (fuzzy) clustering techniques and Dunn's Index is used to analyze hard clustering techniques.
Figure 4 shows the result images of the clustering algorithms.

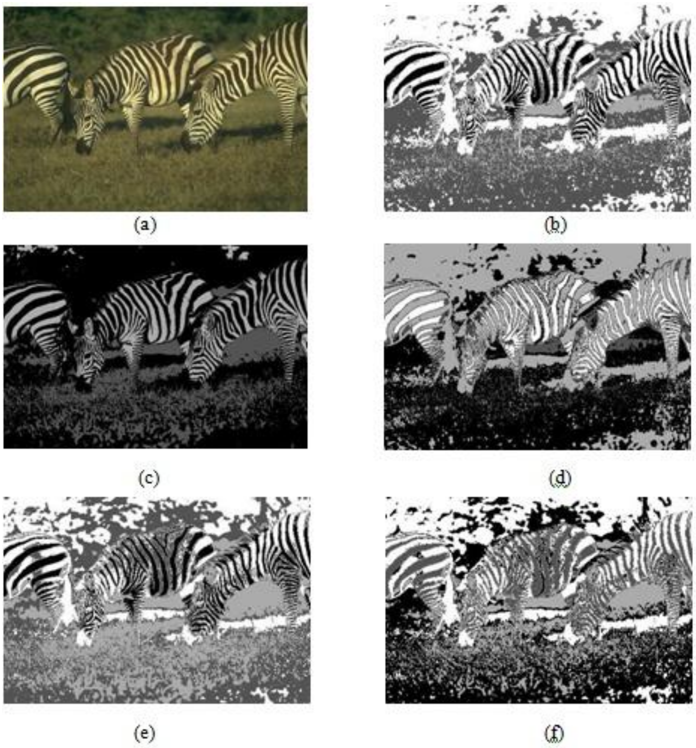
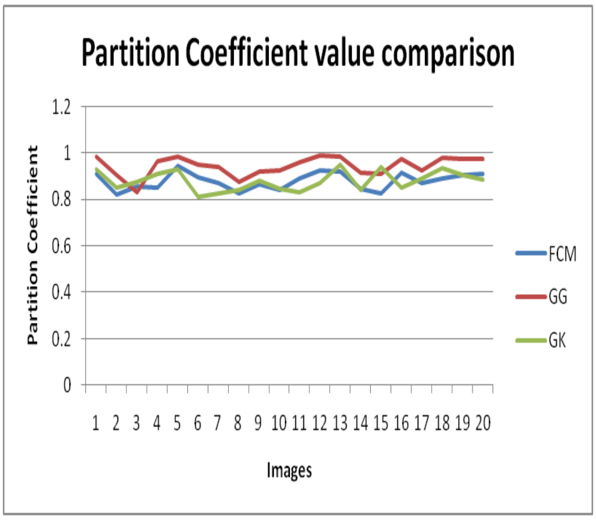


Figure 4: Clustering technique outputs: (a) Original image (b) FCM (c) Gath-Geva (d) K-means (e) Gustafson-Kessel (f) K-medoid

Quantitative results for soft clustering techniques are shown in figure 5.



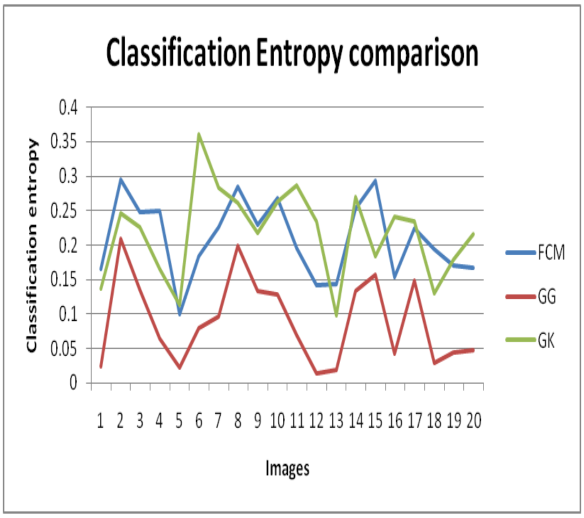


Figure 5: Partition Coefficient values and classification entropy values comparison for soft clustering techniques.

Value of Partition Coefficient lies between 0 to 1. This parameters show amount of overlapping of clusters. Higher value of Partition coefficient represents less overlapping i.e. better clustering. So Partition Coefficient values clearly shows Gath-Geva makes less overlapped clusters i.e. gives better partitioning. Value of Classification Entropy lies between 0 to 1. It measures fuzziness of clusters. Lower value of Classification Entropy shows better clustering. So from the Classification Entropy graph it can be clearly seen that Gath-Geva perform much better than FCM and Gustafson-Kessel.

Quantitative analysis for hard clustering techniques is shown in Figure 6.

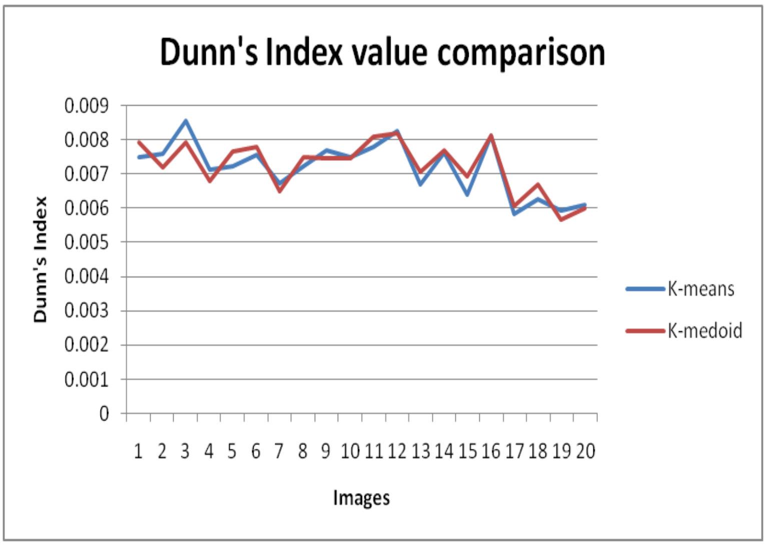


Figure 6: Dunn's Index value comparison for hard clustering techniques.

From Dunn's Index graph it can be seen that K-means and K-medoid are performing approximately equal. As both are showing approximately equal level of Dunn's Index.

V. Conclusion

This paper presented analysis of various image segmentation techniques. Otsu, Improved image segmentation technique based on Otsu, Image thresholding based on standard deviation, Bernsen's local thresholding technique, Niblack's local thresholding technique were analyzed in thresholding techniques. Parameters like true positive rate, false positive rate, ROC analysis are used to measure and compare performance of these segmentation techniques. In clustering techniques category FCM, Gath-Geva algorithm, Gustafson-Kessel algorithm, K-means, K-medoid algorithms were evaluated. Parameters like Partition Coefficient, Classification Entropy were used to measure and compare performance of soft clustering techniques i.e. FCM, Gath-Geva and Gustafson-Kessel. Dunn's Index was used to compare hard clustering techniques i.e. k-means and k-medoid. All of these techniques were applied on a data set of 20 images taken from standard Berkley database. In thresholding category Otsu and Niblack gave better results than other techniques and performed much better thresholding. In soft clustering techniques Gath-Geva algorithm performed better than FCM and Gustafson-Kessel algorithm. In hard clustering techniques k-means and k-medoid performed equally good.

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