Performance analysis of medical microscopic image segmentation techniques

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ABSTRACT

Segmentation techniques play an important role in medical image analysis. More research is required to understand the performance of various segmentation techniques on microscopic medical images. In this paper, four segmentation techniques are analyzed to segment the chromosome images. Performance metrics like SSIM, MSSIM are evaluated for Fuzzy C-Means of clustering, K-Means clustering, Kernel weighted Fuzzy C-Means (KWFCM) and Watershed segmentation. These techniques are compared subjectively and objectively. KWFCM is found to be good and suitable for segmentation of chromosomes from the simulation results.

KEY WORDS: FCM, K-Means, KWFCM, Watershed.

1. INTRODUCTION

Segmentation of image is normally used for subdividing some image as constituent fragment while separating the particular image into background and foreground (Sandeep Kaur, 2015). The particular level up to which the subdivision is performed will depend on the halting condition, that is, segmentation must stop at the point when the particular area of our interest in any application is found to be detached. Accuracy of segmentation denotes the failure or success regarding any of the techniques of segmentation (Manisha Sharma, 2012). Segmentation is found to have the impact of detailed evaluation of the image data that divides any particular image into the meaningful and separate parts. The information is drawn out for grouping together the pixels into regions with similarity, in accordance with the images intensity. Catalog consisting approaches of segmentation of image is primarily based on the two properties pertaining to images.

Difference Detecting: This means separating any image on the basis of sudden changes in the intensity (Manisha Sharma, 2012).

Similarities Detection: This means separating a given image into groups which are similar in accordance with some predefined criterion (Manisha Sharma, 2012).

This study objective is splitting any given set having objects or data into a group that represents a group r a subset. Partitioning may be done on the basis of two properties as follows; a) Homogeneity in the groups; b) Heterogeneity among the groups.

2. SEGMENTATION METHODS

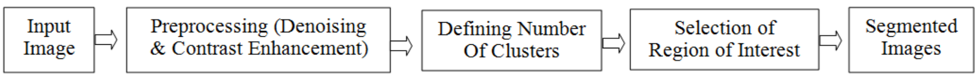


Figure.1. Segmentation Process

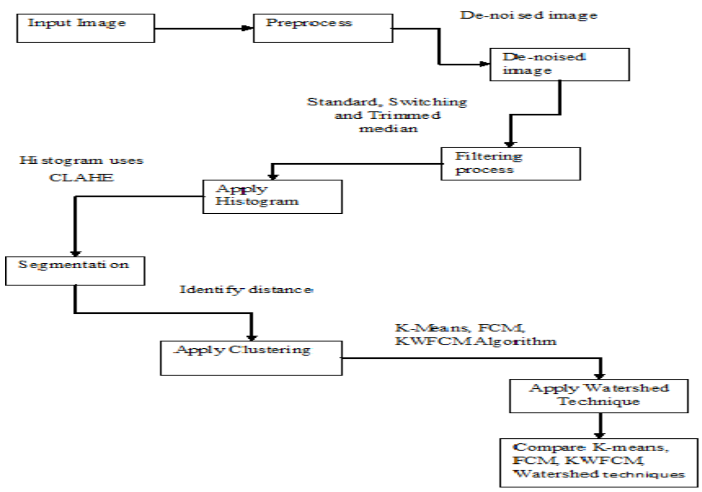


Figure.2. Performance Analysis of segmentation techniques

Clustering or grouping is the process through which partition P pertaining to a set having N objects Xi (i=1,2N). There are several algorithms that have been established in order to cluster the data. Our study involves Fuzzy C-Means grouping. Fuzzy C-Means (FCM) happens to be an unmonitored method of learning that may be

used in classification or data clustering if the count of groups is known. Here, the particular algorithm is presented under:
Step 1: Select number of groups K
Step 2: Fix primary centers of groups c1, c2
Step 3: Categorize each individual vector as the nearest center ci by using measure of Euclidean distance
Step 4: Recalculate the estimates of the group centers ci. Let ci = [ci1, ci2, cin]. T may be calculated by, where Ni will be number of the vectors present in the ith group.
Step 5: In case no cluster center changes in the previous step, then stop. Or else, go to the step 3.

The various segmentation techniques applied to input image and compared the results for various segmentation technique.

K - Means Algorithm: K-Means Algorithm happens to be a very popular method of grouping as it is easy and simple in calculation. This proves to be the simplest and easiest unmonitored learning algorithms which can solve the common issue of grouping problem. It will sort input information points as multiple categories on the basis of their inherent distance between one another. This algorithm attempts to search for natural grouping by assuming certain features (Suchita Yadav, 2013). Here, the K-Means algorithm follows the steps mentioned below:
Step 1: Initiate centroids using k random values
Step 2: Keep the centroid as far away as possible from each group
Step 3: Each point pertaining to the set must be associated closest centroid
Step 4: Association may be done through creation of a loop. K new centroids are obtained at the end of that loop.

Watershed Based Image Segmentation: Watershed Based Image Segmentation may also be referred to as the watershed technique. It is one powerful mathematical morphological application related to segmentation of image. Segmentation based on watershed is famous in certain areas such as medical and biomedical image processing and in computer vision (Nilesh, 2016). And in geographical context, watershed denotes a fold which divides the areas that are drained by varied systems of rivers and so, the technique has been named as Watershed Based Image Segmentation. If in case an image gets viewed as a geographical landscape, watershed lines determine boundaries that separate the regions of image. The transformation of watershed segmentation calculates catchment basis and the ridgelines, also called watershed lines, wherein the catchment basins correspond to image zones while watershed lines correspond to region boundaries. A block diagram pertaining to watershed-based segmentation has been shown in Fig.1. Watershed algorithm has been applied in those methods; it then generates considerable watershed lines related to segmentation. Therefore, for reducing the impact of the rigidness, marker method is applied. The particular processing procedure is known as post-procedure operation pertaining to watershed segmentation.

Kernel Weighted FCM: Kernel Weighted FCM KWFCM approach integrates spatial data and membership weighting related to each group will be changed after considering the group distribution inside the neighborhood (Jolly Francis, 2015). A weighting parameter known as factor of fuzzy tradeoff is being introduced in the objective operation for increasing the segmentations accuracy.

KWFCM Algorithm:
Step 1: Initiate number if groups and the aspiration exercise
Step 2: Add weighing parameter with the aspiration exercise
Step 3: Identify the group centers
Step 4: Determine distance between the data and center
Step 5: Update the membership function
Step 6: When distance becomes minimum, stop the iteration; otherwise go back to step 3

KWFCM method incorporates spatial information and the membership weighting of each cluster is changed after the cluster distribution in the neighborhood is considered (Jolly Francis, 2015). Weighting parameter called trade off fuzzy factor is introduced to the objective function to increase the accuracy of segmentation.

The initial objective function is

$$\text{GFCM} = \sum_{i-1}^{c} \sum_{j=1}^{n} Uijm \| xj - vj \|^2$$

The New objective function is

$$\text{KWFCM} = \sum_{i=1}^{c} \sum_{j=1}^{n} Uijm \| xj - vj \| + Qij$$

Where, $Qij = W_S.W_G$; Ws→ spatial constraint = 1/ (d+1); d→ spatial distance; W_G→ gray level constraint

$$W_G = \begin{cases} 2+lij.Cj \\ 2-lij.Cj \end{cases}$$

lij is the local cardinality

$$lij = \frac{\varepsilon ij}{\sum_{k \in ni} \varepsilon ik}$$

Where, cj is the local coefficient and c is the mean value of cj.

$$\varepsilon ij = \exp[-(cj - \overline{c})]$$

The modified membership function is

$$U_{ki}m = \frac{1}{\sum_{j=1}^{c} (\| xi - vk \| 2 + Fki / \| xi - vk \| 2 + Fj) \wedge 1/(m-1)}$$

Where Fki is the fuzzy factor

$$Fki = \sum_{j \in Ni} 1/(d+1)(1-Uki) \wedge m \| xj - vk \|_2$$

vk is center of the cluster.

Fuzzy C-Means (FCM): FCM separation set of *p* objects *a* {*a* ,*a* ,..., *ap*} in *Rd* dimensional liberty into *c*(1 <*c* <*p*) fuzzy clusters by b = { *b1, b2 , b3 ,..., bc}* cluster centroids or centers. Fuzzy clustering objects are expressed with fuzzy matrix μ with *c* columns and *p* rows in which the number of data objects represents as o and the number of clusters represents as c. μxy, the component in the *y*th column and *x* throw in μ, signifies the association degree or membership function the *y*th cluster among the *x*th object.

The objective of FCM algorithm function is to reduce the following equation.

$$J_m = \sum_{y=1}^{c} \sum_{x=1}^{p} u_{xy}^m \, d_{xy}$$

Where, $d_{xy} = \|a_x - b_y\|$; *m*(*m* > 1) is scalar named as weighting exponent. *M* organizes the resulting clusters fuzziness and *dxy*is Euclidian distance as of object *x a* to cluster center *y b*.

$$Y_j = \frac{\sum_{x=1}^{n} u_{xy}^m a_x}{\sum_{x=1}^{n} u_{xy}^m}$$

The b*y*, centroid of *y*th cluster, is attained as: FCM algorithm is iterative and confirmed as pursue:

a. Choose *m*(*m* > 1); initialize membership function value μxy , *x* = 1,2,...,*n*; *y* = 1,2,...,*c*.
b. Calculate cluster centers b*y*, *y* = 1, 2,..., , c .
c. Calculate Euclidian distance dxy, x=1, 2…, n *y=1, 2,…, c.*

Performance Evaluation Parameters: Performance assessment for quantitatively fixing the state-of-the-art segmentation of image will still require dependable ways. In most of the above mentioned works, performance of segmentation is generally assessed through objective or subjective judgment on several sample images. Similar assessments on a lot of model images may not be generalized in the case of other applications and images. Segmentation assessment metrics may be classified as region-based and boundary-based methods (Manisha Sharma, 2012). The different performance assessment parameters that are used in the evaluation of segmentation of images have been listed below:

SSIM: SSIM (Structural Similarity Index) is one method of measuring similarity among any two given images. In this, image quality measurement is on the basis of a primary uncompressed or deformation-free image, keeping it as reference. Thus, it becomes a complete reference metric.

SSIM is reckoned by the following equation

$$SSIM(x, y) = \frac{(2\mu_x\mu_y+C_1)(2\sigma_{xy}+C_2)}{(\mu^2_x+\mu^2_y+C_1)(\sigma^2_x+\sigma^2_y+C_2)}$$

μ_x→Average of x; μ_y→Average of y; σ^2_x→Variance of x; σ^2_y→Variance of y; σ_{xy}→Covariance of x&y; C_1→ $(K_1L)^2$ & C_2→ $(K_2L)^2$ are two variables to stabilize the division with week denominators; L→ Dynamic range of pixel values; K_1→0.01 & K_2→0.03 by default.

Mean Square Error (MSE): Mean square Error is calculated pixel by pixel by using the following rule.

$$MSSIM(x, y) = \frac{(2\mu_x\mu_y+C_1)(2\sigma_{xy}+C_2)}{(\mu^2_x+\mu^2_y+C_1)(\sigma^2_x+\sigma^2_y+C_2)}$$

M→no. of rows; N→no of columns; GI→Original Image; SI→Segmented Image

MSE should have a lower value to have a higher quality segmented Image.

MSSIM: The Mean SSIM is used to compare local patterns of pixel intensities that have been normalized for luminance & contrast.

The MSSIM can be calculated from SSIM as follows

$$SSIM(x, y) = \frac{(2\mu_x\mu_y+C_1)(2\sigma_{xy}+C_2)}{(\mu^2_x+\mu^2_y+C_1)(\sigma^2_x+\sigma^2_y+C_2)}$$

The MSSIM is calculated by taking mean of SSIM.

UQI: Universal Quality Index is reckoned by substituting the values of C_1 & C_2 as zero & it is given as

$$UQI(x, y) = \frac{(2\mu_x\mu_y)\,(2\sigma_{xy})}{(\mu^2_x+\mu^2_y)\,(\sigma^2_x+\sigma^2_y)}$$

MSE, PSNR of Median Filters: The Standard Median, Switching Median, Trimmed Median Methods Denoised outputs, MSE, PSNR Value represented in this Table.

Table.1. Median Filters

Methods	Input Images	Denoised Images	MSE	PSNR
Standard median			215.49	24.79
Switching median			0.1951	55.23
Trimmed median			212.90	24.85

The various median filter techniques like Standard median, Switching median, Trimmed median denoised output image are implemented in Matlab 2013a. The mean square error and PSNR value will be differ for different median filter.

Table.2. Median Filters

Methods	Input Images	Denoised Images	MSE	PSNR
Standard median			196.7442	25.1918
Switching median			0.1900	55.3434
Trimmed median			195.8272	25.2121

Table.3. Median Filters

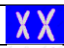
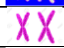
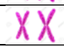
Methods	Input Images	Denoised Images	MSE	PSNR
Standard median			215.4977	24.7964
Switching median			0.1785	55.6149
Trimmed median			144.7416	26.5249

Table.4. Enhanced Histogram Images

Methods	Input Images	Enhanced Images
Histogram		
Histogram		
Histogram		

The Table.4. Shows Enhanced Histogram Images. The histogram is used for color variation.

Table.5. Enhanced CLAHE Images

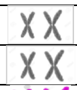
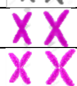
Methods	Input Images	Enhanced Images
Clahe		
Clahe		
Clahe		

The Table.5. Shows Enhanced CLAHE Images. The CLAHE is used for contrast enhancement.

3. SIMULATION RESULTS

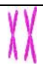
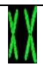
The Various Segmented Techniques Are Implemented in Matlab 2013a. The different segmented output images are represented in table 6.

Table.6. Segmented Images

Methods	Input Images	Segmented Images
FCM		
K means		
Watershed		
KWFCM		

The FCM, K means, Watershed and KWFCM segmented methods output represents in this table 6.

Table.7. Performance Metrics

Methods	Images	Performance Metrics							
		RMSE	PSNR	MSE	AN	AS	MSSIM	SSIM	UQI
FCM		222.3	0.942	4.0781e+05	0.036	97.2585	0.124	0.9377	1.063
		222.4	0.945						
K-Means		222.5	0.962	4.0881e+02	0.027	97.5682	0.126	0.9287	1.066
		222.9	0.963						
Watershed		223.296	0.993	4.0881e+05	0.035	97.9685	0.130	0.9262	1.072
		223.3156	1.100						
Texture Based Analysis		223.456	1.1011	5.0286e+03	0.021	98.2787	0.135	0.9057	1.1103
		223.615	1.1021						
KW-FCM		224.6112	1.1022	5.0396e+04	0.0165	98.3587	0.142	0.9026	1.264
		224.4897	1.1069						

The table.7 shows Different Methods Performance Metrics like RMSE, PSNR, MSE, AN, AS, SSIM, MSSIM and UQI.

4. CONCLUSION

An assessment metric of segmentation of image needs to consider certain effects such as under segmentation, over segmentation, varied number of segments, and inaccurate localization of boundary. Performance appraisal process regarding any given techniques or segmentation programs may be performed using performance metrics. The segmentation performance may be improved through calculation of the performance metrics. Take for instance, lower MSE value indicates higher quality pertaining to any segmented image.

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