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Image Segmentation Using PSO-Enhanced K-Means Clustering and Region Growing Algorithms

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Abstract

Image segmentation is a basic image processing technique that is primarily used for finding segments that form the entire image. These segments can be then utilized in discriminative feature extraction, image retrieval, and pattern recognition. Clustering and region growing techniques are the commonly used image segmentation methods. K-Means is a heavily used clustering technique due to its simplicity and low computational cost. However, K-Means results depend on the initial centres' values which are selected randomly, which leads to inconsistency in the image segmentation results. In addition, the quality of the isolated regions depends on the homogeneity of the resulted segments. In this paper, an improved K-Means clustering algorithm is proposed for image segmentation. The presented method uses Particle Swarm Intelligence (PSO) for determining the initial centres based on Li's method. These initial centroids are then fed to the K-Means algorithm to assign each pixel into the appropriate cluster. The segmented image is then given to a region growing algorithm for regions isolation and edge map generation. The experimental results show that the proposed method gives high quality segments in a short processing time.

Keywords: Image segmentation, K-Means, Particle Swarm Intelligence (PSO), Li's method, Region growing.

تجزئة الصورة باستخدام خوارزمية التجميع *K-Means* المحسنة بأستخدام *PSO* وخوارزمية المنطقة المتنامية

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الخلاصة

تجزئة الصورة هي تقنية أساسية لمعالجة الصور تُستخدم بشكل أساسي للعثور على الأجزاء التي تشكل الصورة بأكملها. يمكن بعد ذلك استخدام هذه المقاطع لغرض استخراج السمات التمييزية، استرجاع الصور، والتعرف على الأنماط. تعد تقنيات التجميع وتزايد المنطقة من طرق تجزئة الصور الشائعة الاستخدام. K-Means هي تقنية تجميع مستخدمة بكثرة بسبب بساطتها وانخفاض التكلفة الحسابية لها. مع ذلك ، تعتمد نتائج K-Means على قيم المراكز الأولية التي يتم تحديدها عشوائيًا، مما يؤدي إلى عدم تناسق في نتائج تجزئة الصورة. بالإضافة إلى ذلك، تعتمد جودة المناطق المعزولة على تجانس الأجزاء الناتجة. في هذا البحث، تم اقتراح خوارزمية K-Means محسنة لتجزئة الصورة. تستخدم الطريقة المقدمة ذكاء سرب الطيور

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(PSO) لتحديد المراكز الأولية بالاعتماد على طريقة Li. يتم بعد ذلك تغذية هذه المراكز الأولية إلى خوارزمية K-Means لتعيين كل بكسل في المجموعة المناسبة. ثم يتم إعطاء الصورة المجزأة لخوارزمية نمو المنطقة لعزل المناطق و توليد خريطة حواف الصورة. أظهرت النتائج التجريبية أن الطريقة المقترحة تعطي مناطق عالية الجودة خلال وقت معالجة قصير.

1. Introduction

Image segmentation is one of the most widely used techniques for classifying the pixels of an image in a decision-oriented application. It divides an image into a number of different regions, so that in each region the pixels have a high similarity and a high contrast between regions. It is a powerful tool in several fields such as health care, image processing, pattern recognition, etc. There are many techniques for image segmentation like edge-based, region growing and cluster-based methods [1].

The pixels that have sharp differences in intensity are represented as segments in edge-based techniques. However, the edges may be broken or incomplete and they cannot provide a clear separation among the segments in the image [2]. On the other hand, region-based techniques are based upon the collection of pixels having similar features, which can be grey level intensity information or color image components. Region based segmentation includes region growing technique. In this method, the entire image is divided into sub regions or large regions, using predefined criteria in a bottom-up fashion. In other words, the basic idea is to group a collection of pixels to form a region based on some similar properties [3].

Clustering-based techniques are the most efficient segmentation methods [4]. There are numerous methods of clustering, and the K-Means clustering algorithm is one of the most common methods [5]. K-means is an unsupervised algorithm that attempts to divide a group of data objects into K clusters based on the distance between the data object and the K centroids. In the case of image segmentation, a set of image pixels are clustered in a manner such that, pixels within a cluster have more similarity in comparison with pixels in another cluster [6]. However, there are some limitations in the K-means based methods that need to be solved; for example, due to its greedy nature, it is sensitive to centres' initialization and it is also sensitive to outliers [1]. There have been many works in the area of image segmentation by using K-means algorithm and many researchers are trying to solve K-Means shortcoming and enhance its results. Dhanachandra *et al*. (2015) [5] used the subtractive clustering method to generate the initial centers which are then used with K-Means algorithm for the segmentation purpose. Khan *et al*. (2017) [1] suggested an improved K-Means clustering algorithm for image segmentation by employing an adaptive histogram-based initial parameter estimation procedure. Zheng *et al*. (2018) [7] proposed an adaptive K-Means image segmentation method. This method firstly transforms the color space of images into LAB color space. The luminance value is then set to a predefined value to reduce the effect of light on image segmentation. After that, the equivalent relation between K values and the number of connected domains after setting threshold is used to segment the image adaptively.

Swarm intelligence (SI) is an artificial intelligence mainly based on decentralized, self-organized systems' collective actions. Usually, SI systems are made up of a population of simple agents communicating with each other and with their environment locally. Examples of SI techniques are ant colony optimization, Particle Swarm Optimization (PSO), bee colony optimization, stochastic diffusion search, and bacterial foraging optimization. PSO is modelled on the social behaviour of birds' flocks. This algorithm is initialized with a population of random solutions, called particles. Each particle flies dynamically in the search space with a given velocity. These dynamic changes are based on the past behaviours of the particle itself and other particles in the population [8]. Kim *et al*. (2018) [9] tried to develop a clustering-based segmentation method based on the PSO to initial K-Means parameters automatically. In the PSO, the particle group motion is implemented by pixel-by-pixel passage through the image. Distance function minimization is used as an objective function of

PSO optimization process. An object in an image characterized with relative color uniformity, i.e. if the distance function for pixels a and b that belong to one object tends to minimum, their color function also tends to minimum. Pambudi (2018)[10] used PSO for initial centroid computation where for each particle the fitness value is computed. Fitness function in this research is the minimum value of SSE (Sum Square Error).

The main problem is finding the accurate regions in the image and generating the edge map. Although different works [9, 10] tried to find the accurate regions by using PSO for K-Means initial parameters' settings (i.e., centroid initialization), these works did not take into account the relation between the resulted cluster and the background. So, this research gap is exploited in this work and Li's method is utilized as a fitness function of PSO. Li's objective function helps in increasing the variance degree between the given cluster and the background. This paper focuses upon the clustering algorithms initialization parameters for image segmentation. It devises a procedure to automatically determine initial cluster centers of the clustering algorithm, ensure short segmentation time, and get high quality segments. The structure of the remainder parts of the paper is as follows: The proposed segmentation method is described in details in Section 2. The experimental analysis and achieved results are shown in Section3. Finally, work conclusion and ideas for future work are presented in Section4.

2. The Proposed Method

As shown in Figure (1), the proposed segmentation method involves three main stages: image loading and down-sampling, image clustering, and region isolation. The detailed description of each stage functions is given in the next subsections.

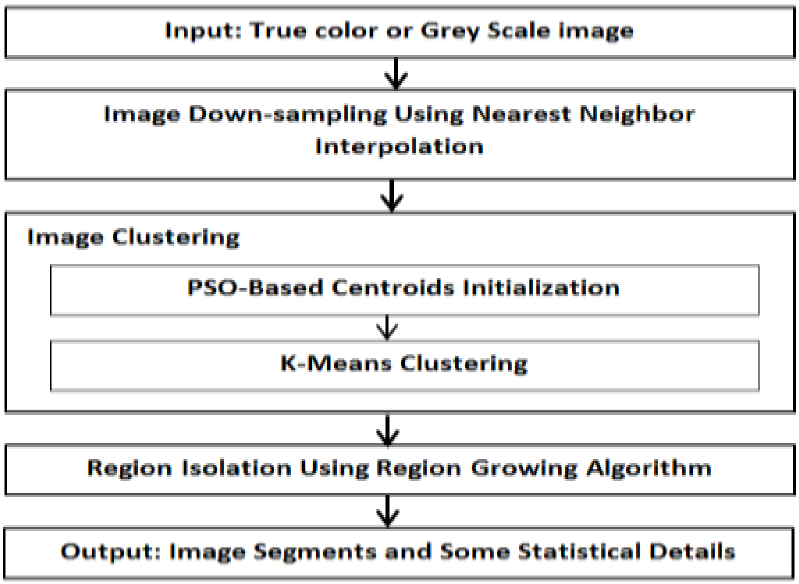


Figure 1-General design of the proposed segmentation method using PSO-Enhanced K-Means clustering

2.1 Image Loading and Down-Sampling

In this stage, the image is firstly loaded. After that, the basic Red, Green, Blue (RGB) colors are retrieved from each pixel in the true color image. Since the proposed method is based on techniques with iterative behaviour, the image must be down sampled to speed up the segmentation process. Given an image (I) with size (w×h) and required scale factor (sf), the image is down sampled to the new size ((w×sf)× (h×sf)) using nearest neighbour interpolation method. The following equation is used with nearest neighbour interpolation [11]:

$$I_{new}(x,y) = \sum_{i=-k_s+1}^{k_s+1} \sum_{j=-k_s+1}^{k_s+1} I_{org}(i + x_o, j + y_o)\, h(i - F_x)\, h(j - F_y) \quad (1)$$

where (x, y) are the new coordinates of the interpolated pixel, (x_o, y_o) are the original coordinates of the image pixel, $I_{new}(x,y)$ is the interpolated pixel value, $I_{org}(i+x_o,j+y_o)$ is the original pixel value, h represents the interpolation function, (i, j) denotes the boundary of the function (with kernel size=k_S) in X and Y coordinates, respectively, and F_x represents the position of the interpolate pixel relative to its neighbors; it is calculated by applying the following steps:

(a) Calculate the exact position by multiplying the neighbor's pixel coordinates (i, j) by magnification ratio k_x (i.e. the ratio between old size and new size).

(b) Extract the integral part of F_x.

(c) Find the position of the new pixel by subtracting (b) from (a).

Nearest neighbor interpolation uses the following interpolation kernel [11]:

$$h(d) = \begin{cases} 0 & |d| \geq 0.5 \\ 1 & |d| < 0.5 \end{cases} \quad (2)$$

where *d* is the distance between grid pixel and interpolated pixel.

2.2 Image Clustering

Image clustering is performed to divide the image into K number of segments with some homogenous colors. K-Means clustering is utilized for the clustering task. However, the main problem of K-Means algorithm is defining the initial values of clusters' centroids. To avoid such problem, centroids' values are initialized using swarm intelligence. Swarm intelligence offers speed in convergence during the search for the optimal initial values of each cluster centre. In addition, using predetermined value for clusters' centres will ensure that the same segmentation result is reached every time K-Means runs.

2.2.1. PSO-Based Centroids Initialization

PSO algorithm is utilized for finding the optimal centroid values from which K-Means will start the clustering process. The objective function that is used during optimization process is based on the approach proposed by Li [12]. The main reason behind utilizing Li's method as an objective function for the PSO is that this method preserves the relation between the foreground and background when finding the optimal value through increasing the variance between them, as in the following equations [12]:

$$J(\beta, c) = \beta\left(\sigma_1^2(c) + \sigma_2^2(c)\right) + (1 - \beta)\sigma_D^2(c) \quad (3)$$

and

$$\sigma_D^2(c) = \sigma_1(c)\sigma_2(c) \quad (4)$$

where $\sigma_1(t)$ is the standard deviation of the foreground (the cluster).

$\sigma_2(t)$ is the standard deviation of the background (other clusters).

$\sigma_D^2(t)$ is the measure of the variance degree between the given cluster and the background.

β is a parameter that represents the weight balance to determine the contributions of variance discrepancy and variance sum in centre computation.

To obtain the optimal cluster centroid (c^*), Li proposed to minimize the following criterion [12]:

$$J(a, c^*) = Min_{0 \leq c \leq L-1}\, J(\beta, c) \quad (5)$$

The proposed PSO-based centroid initialization approach can be summarized with the following steps:

Step1: The population of the swarm consists of N particles. The initial position of each particle (P_i) is calculated as follows:

1) Find the minimum and maximum values for each color channel (i.e., red, green, blue) in the image.

2) Compute the range of each channel.

3) For each channel, divide the range into K regions. Each region with length equals to (Range/K).
4) Define three parameters (cr1, cr2, cr3) to determine the color intensity from which PSO population will be initialized for the three color channels. The first particle will have a position vector equals to 0 for the three channels.
5) Start PSO optimization with an initial particle position equals to 0 for the three channels. The other particles' values are then determined from the previous particle with increment values equal to cr1, cr2, and cr3.
Step2: Particles' velocities (V_i) are then updated as in the following equation [13]:

$$V_i = wV_i + \alpha_1(P_i - Lbest) + \alpha_2(P_i - Gbest) \quad (6)$$

where $\alpha_1$and α_2 represent learning speed, w is the inertia factor used to prevent the sudden change in particle position, Lbest is the best particle position in the given iteration, and Gbest is the best particle position for all iterations.
Step3: After that, particles' positions are updated using the following equation [13]:

$$P_i = P_i + V_i \quad (7)$$

Step4: Repeat steps 2 and 3 until the number of iterations reaches the maximum iterations number.
Step5: At the end of the optimization process, the global best particle (Gbest) within each region will be considered as the initial centres' values for that cluster.

2.2.2. K-Means Clustering

In this stage, the segmentation process is performed using K-Means with initial centroid values that are defined using PSO optimization. Clustering process involves the following steps:
Step1: Define the initial centres' values using Gbest values that are obtained when applying PSO within each color region.
Step2: For each pixel in the image, compute the distance of that pixel from the centre of each cluster using city block distance metric.
Step3: Assign each pixel to the cluster that gives the minimum distance.
Step4: Re-compute cluster centres by summing up pixels' values that are grouped within that cluster and dividing the sum by the total number of these pixels.
Step5: Repeat steps 2 to 4 until the total number of iterations is reached or the centres' values of all clusters do not change more than $change_{th}$, where $change_{th}$ represents the minimum value for the acceptable change in clusters' centres.

2.2.3. Region Isolation

In the region isolation stage, the required regions are extracted from the segmented image using a region growing algorithm, which has the following steps:
Step1: Load the image that is resulted from clustering stage.
Step2: Calculate minimum and maximum pixel intensity values in that image.
Step3: Choose the number of regions to be segmented.
Step4: Set threshold value; T (T value ranges from 5% to 10% of max-min intensity).
Step5: Get initial position (i.e., coordinates for initial seed position). Define position of the required region by clicking in the image. Get the pixel position concerning the current axes coordinates, and get the initial pixel value.
Step6: Add the initial pixel to the queue, where the first queue position determines the new values.
Step7: Check the neighbours for the current position within (x, y) bounds and the given threshold value (T). Current pixel is true, if all properties are fulfilled. Then add the current pixel to the computation queue and then repeat step 7 (recursive) until false condition is reached.

Step8: Extract the polygon vertices by the loop through each slice and use an enclosing polygon to fill the holes inside the mask.
Step9: Finally, extract the regions with an edge map and calculate segmented region statistics (min, max, average intensity, no. of pixels, maximum area, max density area, etc).

3. Experimental Results

3.1. Test Material

To evaluate the efficiency of the proposed method, two types of images are used as shown in Fig. 2. The first type is the standard test images where Lena and Mandril color images are used. Medical images are used in the second type, represented by brain tumor image and chest X-Ray image.

(a) **(b)** **(c)** **(d)**

Figure 2-Sample test images (a) Lena image, (b) Mandril image (c) brain tumor image (d) chest X-Ray image.

3.2. Image Clustering Results

Experiments were conducted to determine the optimal parameters' values of the proposed segmentation method. It was found that, when N=10, MaxEpochs = 10, w=1, c1 =0.5, c2=0.5, β =0.5, sf=0.5, cr1=7, cr2=7, cr3=7, $change_{th}$ =10, and Noitr=10, then the method gives the best results; for this reason, these values are adopted in the experiments.
Homogeneity measure was used to measure the efficiency of the resulted clusters. Homogeneity gives an indicator about cluster color connectivity. For image (I) with size (w×h), homogeneity (I) can be calculated as [14]:

$$Homogeneity(I) = \sum_{i=0}^{w-1}\sum_{j=0}^{h-1}\frac{I(i,j)}{1+|i-j|} \quad (8)$$

Tables 1 to 4 show the results of applying the original K-Means and PSO-enhanced K-Means on the different test images, with K= 2, 3, 4, and 5, respectively. The tables also demonstrate the required number of iterations ($I_{No.}$) to reach the stop condition of K-Means algorithm and the resulted homogeneity, for the two cases.

Table 1-Results achieved when applying original K-Means and PSO-enhanced K-Means on test image (a).

K	Original K-Means	$I_{No.}$	Homogeneity	PSO-enhanced K-Means	$I_{No.}$	Homogeneity
2		4	298788.339649134		3	299344.4630347

3		4	304987.509846297		1	303700.003795631
4		4	301418.433460319		2	301018.9555654
5		3	300534.982975075		2	300744.159972376

Table 2-Results achieved when applying original K-Means and PSO-enhanced K-Means on test image (b).

K	Original K-Means	I_{No}.	Homogeneity	PSO-enhanced K-Means	I_{No}.	Homogeneity
2		3	667450.163641218		2	667080.42783932
3		4	674941.240256723		2	678448.187778222
4		4	673231.299859026		2	677041.102130586

5		4	676718.298411401		2	676874.071357672

Table 3-Results achieved when applying original K-Means and PSO-enhanced K-Means on test image (c).

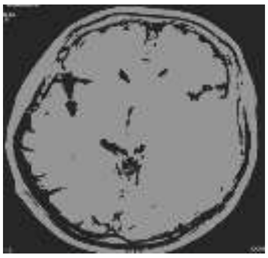
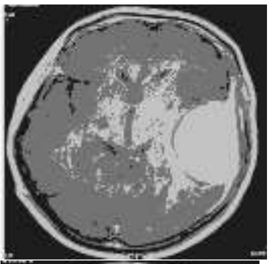
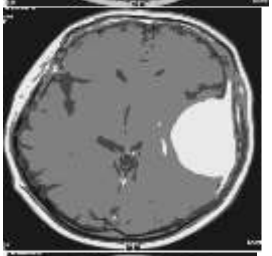
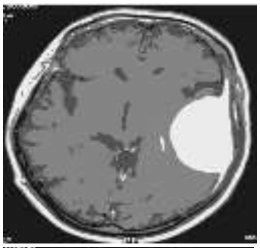
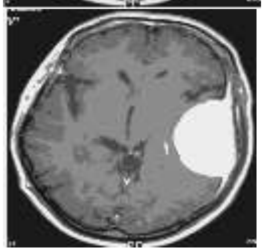
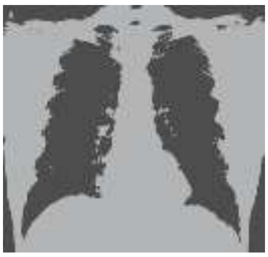
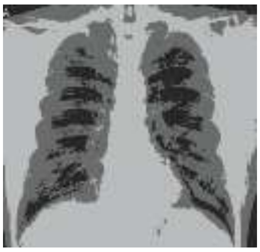
K	Original K-Means	$I_{No.}$	Homogeneity	PSO-enhanced K-Means	$I_{No.}$	Homogeneity
2		2	1143866.0774819		1	1145685.24643353
3		4	1224098.7692463		3	1214651.12195197
4		4	1210824.68384515		1	1220987.09349022
5		3	1233146.5128634		2	1241906.2160166

Table 4-Results achieved when applying original K-Means and PSO-enhanced K-Means on test image (d).

K	Original K-Means	$I_{No.}$	Homogeneity	PSO-enhanced K-Means	$I_{No.}$	Homogeneity
2		4	1028059.67549193		3	1022436.68109397

3		3	1024615.47114165		2	1024650.66958711
4		3	1025813.14603466		1	1027078.78348083
5		2	1031288.46060187		1	1035866.24365044

As it is seen in tables 1 to 5, PSO-enhanced K-Means can give more homogenous segments with a number of iterations that is lower than that obtained using the original version of K-Means algorithm. On the other hand, the time is another important factor to evaluate any segmentation algorithm performance. Table 5 shows the estimated time for the original and PSO enhanced K-Means.

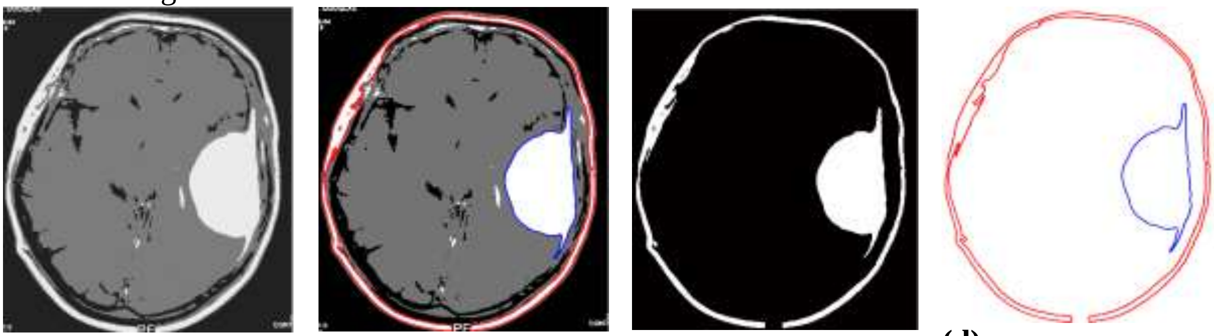
Table 5-Time (in seconds) estimated when applying original K-Means and PSO-enhanced K-Means on the test images with different K values.

	(a)		**(b)**		**(c)**		**(d)**	
K	**Original K-Means**	**PSO-enhanced K-Means**	**Original K-Means**	**PSO-enhanced K-Means**	**Original K-Means**	**PSO-enhanced K-Means**	**Original K-Means**	**PSO-enhanced K-Means**
2	0.1147919	0.5076629	1.1956567	0.8883883	0.2539589	0.1870079	0.1461633	0.1582782
3	0.1790622	0.1049761	2.1454233	1.2960322	0.4603051	0.4971577	0.2184357	0.1764872
4	0.1997782	0.1523056	2.2545289	1.4744985	0.5649312	0.3458046	0.2083695	0.1964142
5	0.2204214	0.2822421	2.5714693	1.8929184	0.6405380	0.5158165	0.2537339	0.2447927

The time is highly reduced when using PSO enhanced K-Means, as it is clearly illustrated in Table 5. Substantially, the homogeneity and time values varied with different K values. This reflects the fact that more segments can be reached with different K values. Hence, the time of PSO optimization increases as K increases while the homogeneity values decrease.

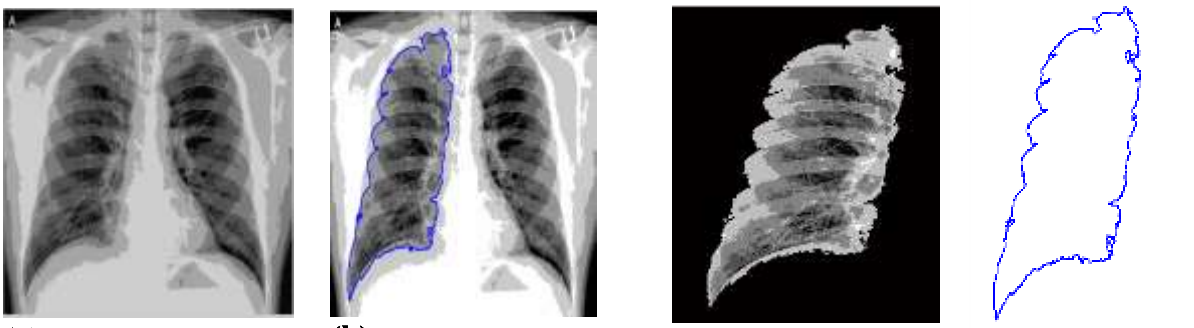
3.3. Results of Region Isolation

Figures 3 and 4 show the results of the region isolation stage when applied on the two test images which resulted from the clustering stage. On the other hand, Table 6 provides some statistics of the isolated regions that are shown in Figs. 3 and 4. As it is clearly shown in these tables, high quality regions can be extracted from the segmented images for the two different medical images.



(a) **(b)** **(c)** **(d)**

Figure 3-Region isolation results when applied on the segmented brain tumor image (a), segmented image (b), the selected two regions (red and blue colors) (c), and the isolated regions (d) edge map.



(a) **(b)** **(c)** **(d)**

Figure 4-Region isolation results when applied on the segmented chest X-Ray image (a), segmented image (b), the selected region (blue color) (c), and isolated region (d) edge map.

Table 6-Some statistics of the segments resulted from region isolation.

Image	**Selected region**	**Initial seed point coordinate**	**Initial Pixel value**	**No. of pixels within specific intensity range**	**Min intensity value in the input image**	**Max intensity value in the input image**	**Average intensity**	**No. of polygon vertices**
(c)	Blue region	(506,618)	235	53121	234	235	235.0015	1085
	Red region	(678, 46)	235	43495	123	236	234.2795	5194
(d)	blue region	(295,207)	85	85811	8	167	90.70	2137

4. Conclusions and Future Work

A method for image segmentation using the clustering-based technique is proposed in this paper. PSO algorithm helps in finding the optimal centroid values from which K-Means algorithm starts clustering. Li's method was employed as an objective function for PSO because it can observe the relation between cluster object and the background (other clusters). Region growing algorithm was applied to isolate the required regions from the segmented image. The combination of K-Means, PSO, and Li's method helped in obtaining more homogenous segments everywhere in the clustered image, with a fewer number of iterations and reduced processing time. The test results showed that the proposed method gave homogenous regions with statistical information which are useful to be used for further analysis of the extracted regions. As a future work, machine learning techniques for image segmentation can be utilized with PSO; for example, using PSO to initialize parameters of semantic segmentation.

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