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Pancreatic Tumor Segmentation Based on Optimized K-Means Clustering and Saliency Map Model

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Abstract: ***Segmentation of positron emission tomography (PET) plays a major role in research and clinical applications. The segmentation of pancreatic tumors using PET / CT is challenging due to a significant amount of noise that may result in serious segmentation inaccuracies. The evaluation of the results of segmentation in medical imaging is due to the presence of a gold standard. Therefore, the performance evaluation of these methods would be necessary. This paper suggested a new object segmentation method that is based on K-means clustering with Saliency Maps. The K-means clustering approach restricts every pixel of the image that belongs to a single cluster. One drawback with using the K-means algorithm to segment objects is that segments are not connected and can be widely scattered. It is known that using saliency region, the approximate location of the desired object in the map can easily be identified. In this proposed method, the saliency map is used to distinguish the desired object cluster from the image from the background cluster, and then, to map the object clusters together Experimental results shows that the proposed algorithm outperforms dramatically in terms of visual plausibility and computational cost compared to state-of -the-art methods and achieves excellent performance for object segmentation.***

Keywords : Clustering, Contrast, Spatial, Saliency, PET/CT.

I. INTRODUCTION

Image segmentation is a significant topic for medical image processing as a basis for tasks of high-level image analysis such as object recognition, image retrieval, and image analysis and so on. In particular, segmentation of medical images are considered as a challenging task. Salient objects are measured important for further image analysis in such instances. Saliency refers to the ability for further processing to choose relevant visual information. The system has been shown to be beneficial to both human and machine vision. Detection of salient object simulates the human visual system by automatically identifying and segmenting the regions[1]. Each pixel in the saliency map represents its probability to be salient. The function makes image representation more meaningful and simpler like Object segmentation for further research. Many image saliency detection algorithms have been proposed over the past couple of decades. Most of these methods represent pixel-grid images of the input. There are two drawback of saliency detection method based on pixel-grid. For the images with large salient regions, this performs poorly. Secondly, this method also suffer from disordered background [2].To overcome the above drawbacks, this paper seeks to highlight the salient region in PET/CT images using a cluster-based algorithm.

The proposed method calculates pixel saliency values based on K-means clusters. Local and global contrast helps to highlight important objects so that differences in contrast and location of pixels are considered as the basis of the cluster. Normalized vector pixels are clustered by means of k-means based totally on contrast and spatial features. This approach is called Clustering Contrast Saliency because with the help of cluster contrast, the saliency map is estimated.

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II. STATES OF PET/CT IMAGE SEGMENTATION METHODS

Numerous segmentation techniques are utilized and classified into manual, semi-automatic and automatic techniques. Clustering method tried to access the connection between image pixels by grouping the pixels into clusters in such a way that pixels within a cluster are identical to pixels belonging to different pixels. Clustering refers to grouping of pixels according to certain object properties. To make segmentation more effective, a number of clustering techniques have been implemented. K-means, which is commonly used for object segmentation, are the most well-known and classical partitioning algorithms. In K-means clustering approach, it limits each pixel of the image fit into entirely just one cluster [3]. The clustering techniques that are included in this paper are K-means clustering, Fuzzy C-means clustering and Salient based K-means clustering contrast saliency map method.

A. Fuzzy C-Means (FCM) Algorithm

In FCM, the data components are clustered dependent on the connection value allocated to every one of them. As indicated by the rule of the least square, iterative optimization is utilized for optimizing object function, and the last division of data is got after calculation. Let X = (x_1, x_2, x_N) indicates an input image with N pixels to be partitioned into 'c' clusters, where x_i means multispectral data.

FCM depends on minimization of the accompanying objective function:

$$J = \sum_{j=1}^{N} \sum_{i=1}^{c} u_{ij}^{m} \, ||x_j - v_j||^2$$

From the above formula 'u_{ij}' is the degree of enrollment of 'x_j' in the cluster 'i' and 'v_i' is the i^{th} bunch cluster center. '||' means a distance metric symbol and 'm' is a constant variable, which controls the fuzziness of the subsequent segment. This approach is assisted through an iterative streamlining of the target work showed up in above condition, with the modify of membership functions 'u_{ij}' also the cluster center 'v_i' depends upon the going with two functions.

$$u_{ij} = \frac{1}{\sum_{k=1}^{c} \left(||\frac{x_j - v_i}{x_j - v_k}||\right)^{2/(m-1)}}$$

$$v_i = \frac{\sum_{j=1}^{N} u_{ij}^{m} x_j}{\sum_{j=1}^{N} u_{ij}^{m}} \qquad i = 1,2, \ldots \ldots \ldots c$$

The degree of each pixel is calculated by v_i for different center in every process of clustering. This iteration will stop when $(j_i - j_{i-1}) < \varepsilon$, where 'ε' is an extinction condition [4].

B. K-Means Clustering Algorithm

K-means clustering partitions an input data into a 'k' number of clusters. A given set of data is classified into k number of disjoint cluster. K-means algorithm consists of two separate phases. First step calculates the k centroid value. Second step takes each point to the cluster, which has adjacent centroid from the particular data point. Many methods are available to identify the distance of the close centroid. An Euclidean distance approach is most used method for calculating the distance among the centroids. After completing the grouping process this method again, calculate the new centroid. Therefore, it is an iterative method. Now consist an input image with resolution of x×y as well as the image has been grouped into 'k' number of cluster. Here, p(x, y) is an input pixel that is called as cluster centers to be a cluster with ' ck. ' K-means clustering algorithm is described as follows:

- First, define the number of cluster 'k' and initialize the cluster center point 'ck'.
- Evaluate the Euclidean distance'd' between the center and every pixel of an input image by using the below equation.

  $$d = \text{II } p(x, y) - ck \text{ II} \qquad (1)$$

- Allocate every pixels to the adjacent center depend on the distance'd'.
- After completing the above step again compute new center point by using the below equation.

  $$ck = \frac{1}{k} \sum_{y \in ck} \sum_{x \in ck} p(x,y) \qquad (2)$$

- Execute above steps until the closing value is obtained.
- Reform the cluster pixels into image.

In this clustering method, the result is based on the initial centroid value but mostly it has been chosen randomly. Therefore, if it is randomly selected, it will get dissimilar result for various initial centers. Therefore, this point chosen process is very significant to get the accurate segmentation results also computational difficulty is one more procedure that need to think while planning the K-means clustering approach. It depends on the amount of data elements, amount of clusters as well as number of iteration. To avoid these issues, contrast stretching and subtractive clustering approaches are utilized to compute the initial center in the proposed algorithm [5].

C. K-Means Clustering Contrast Saliency Method

Saliency method magnitudes the feature channels of pixels into the histogram pattern to calculate the spatial contrast variation as well as evaluate the saliency of the pixel concerning different pixels in the whole image. Nevertheless, the evaluated feature appropriations utilizing histogram are discontinuities at the container edges. So, the proposed method employs clustering to evade the discontinuities at the container edges as well as herein K-means is utilized. For initial centroid calculation below, steps are carried out.

- ***Contrast Stretching***: It is done by stretching and compression process. By applying this technique, the pixel range of lower threshold value and upper threshold value will be mapped to a new pixel range and stretched linearly to a wide range of pixels within new lower stretching value, and the remaining pixels will experience compression.

- ***Subtractive clustering:*** Subtractive clustering is a method to find the optimal data point to define a cluster centroid based on the density of surrounding data points.

From the above procedures, the quantity of the cluster centers and their starting location are evaluated. This circulates the data space to the lattication point and determines the possibilities for each data location based on its space towards the actual data spot. Therefore, the lattice point through numerous data point nearby will have extreme possible rate. Thus, this lattice point with maximum latent value will be choosing as primary cluster center. So subsequent for choosing the first cluster center, it will try to find the second cluster center by calculating the highest potential value in the other lattice points. As lattice spots close to the first cluster center point will decrease its possible value, after that cluster center point will be lattice with numerous data position close by other than primary cluster center lattice point. Subsequently this process of obtaining new cluster center point as well as decreasing the possible of nearby lattice spot recur until potential of all lattice points reduces lower a threshold rate. Consequently, this technique is one of the easiest as well as efficient techniques to identify the cluster centers [6]. However, with raise in the dimension of data, its calculation difficulty raises exponentially. In this way, subtractive clustering technique illuminates the computational technique related with peak strategy. It utilizes data points as the contender for cluster points and the calculation of this technique is relative to the issue size.

Consist a group of 'n' data values: $X = \{x_1, x_2, x_3 \ldots x_n\}$.

After that, every value is consisted as a probable cluster center point. The probable data point's x_n is described as:

$$P_n = \sum_{i=1}^{n} e^{\frac{-4xn-x_i^2}{r_a^2}} \quad (3)$$

In the above formula, ' ra ' is the cluster radius of the hyper sphere in data space, and it is also a positive constant used to define the nearby area. Later than determining the potential of each data spot, pick the data spot as the primary cluster center with the greatest potential. Now consist 'x_1' also 'P_1' as main cluster center as well as its consequent potential correspondingly. Then modify the potential of every data point through the below equation.

$$P_n = P_n - P_1 e^{\frac{-4xn-x_1^2}{r_b^2}} \quad (4)$$

In the above equation, 'r_b' is the extreme circle consequence span in pixel place as well as it is a positive consistent. At this time, a measure of latent is deducted since every data spot while a function of distance from the cluster center at starting point. Therefore data point close to the main bunch focus will contain extraordinarily diminished latent moreover consequently this method has a smaller amount of opportunity in support of choose as subsequent cluster center point. Subsequent to computing overhaul capability of every point, locate subsequent most notable possible as the subsequent cluster center [7]. Thus above procedures proceed until an adequate amount of cluster center is formed.

- ***Cluster-based Saliency Cues:***

In input PET/CT images, M is the number of objects '$\{I^j\}_{j=1}^{M}$' along with N is the amount of pixel in given PET/CT images. The input image pixel set is '$\{p_i^j\}_{i=1}^{N_j}$' with index 'i' in the image. It obtains 'K' clusters '$\{C^k\}_{k=1}^{K}$'. In this process, clusters are indicated by a set of 'D'-dimensional vectors '$\{\mu^k\}_{k=1}^{K}$', in which 'μ^k' denotes the cluster center associated with the cluster 'C^k'. 'n^k' is the pixel amount of cluster 'C^k'.

i. Contrast Prior Calculation: It stands for the visual feature individuality on the PET/CT images also the contrast dimension mechanism suggests the human visual accessible fields. The contrast prior 'wc(k)' of cluster 'Ck' is to be described using its contrast attribute to every further clusters:

$$w^c(k) = \sum_{i=1, i\neq k}^{K} \left(\frac{n^i}{N} ||\mu^k - \mu^i||_2\right) \quad (5)$$

Here, Euclidean Distance (ED) norm is utilized for calculate the feature space distance value

ii. Spatial Prior: It stands for the location i.e., position prior lying on the cluster spot which is an overall middle bias on the number of targets on the PET/CT image. The spatial prior 'ws(k), of cluster 'Ck' is described as:

$$w^s(k) = \sum_{j=1}^{M} \sum_{i=1}^{N_j} [\aleph(||z_i^j - o^j||^2 | 0, \sigma^2) . \Delta [b (p_i^j - C^k)] \quad (6)$$

From the above formula, '$\aleph$' means Gaussian kernel that calculates the ED among pixel 'z_i^j' as well as the cluster center 'o^j', the variance 'σ^2' is the regularized anatomy of objects. 'Δ' means delta function, which associates the pixel 'p_i^j' and the cluster index b '(p_i^j)' [8].

iii. Cluster saliency map: This step merge the saliency map acquired from the two priors above to build a cluster saliency map

$$Sj = w^c(k) + \lambda w^s(k) \quad (7)$$

At this time, 'λ' is a parameter among 0 and 1 which verifies the relative significance of spatial allocation.

III. A NOVEL METHOD FOR AUTOMATED PET/CT IMAGE SEGMENTATION

In many cases of clustering algorithms, the medical image is constantly more segmented. Salient objects detection can offer precious data to improve the segmentation performance [9]. Segmenting the salient vectors as a substitute of explicitly segmenting the image is an effective approach. This section explains the functioning of the proposed image segmentation procedure. Below figure depicts block diagram of the suggested segmentation method. Proposed method involves the following processes:

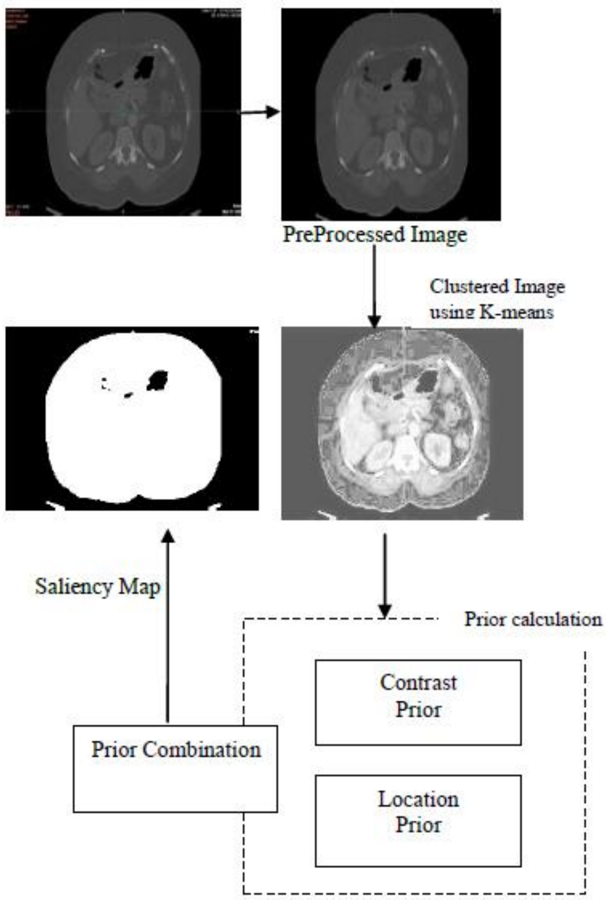

Fig1.Framework for Proposed Method

Proposed Algorithm Steps:

- Step1: Clustering image by using k-means clustering algorithm.
- Step2: Computing the contrast prior for each cluster
- Step3: Computing the spatial prior for each cluster

- Step4: After calculating the two priors, namely spatial and contrast, consolidate the priors with utilizing point wise multiplication.
- Step5: For every pixel getting the last single saliency map.

IV. RESULT AND DISCUSSION

This research is an attempt to compare some image segmentation techniques. The techniques considered in this present research work are K-means clustering, FCM, and K-means clustering based saliency map segmentation algorithms. All the techniques are compared and analyzed for best results and maximum accuracy.

Table 1: Comparison of Results of K-means, FCM, and proposed segmentation algorithms

IMAGE	K-means clustering		FCM		Proposed	
	RI	GCE	RI	GCE	RI	GCE
IM1	10.0766	4.8469	11.0766	5.7469	15.3583	4.8469
IM2	10.4472	4.5092	10.4472	5.5791	14.8614	4.5092
IM3	11.3871	4.0695	11.3871	4.1165	15.6706	4.0695
IM4	6.9675	3.7343	6.9675	5.7343	9.9051	3.7343
IM5	9.729	5.8094	12.1487	5.8422	12.1487	5.8094
IM6	10.2628	6.3885	12.6332	6.3885	12.6332	6.3885
IM7	11.1284	5.8422	13.7627	6.8094	13.7627	5.8422
IM8	12.5049	7.1039	14.0285	7.1039	14.0285	7.1039

In Table 1, results shown that the RI gains and GCE decreases to PET/CT scan images for our proposed technique [10]. The above results and analysis illustrates that the proposed method outperforms over the existing cluster based segmentation methods.

Evaluation Parameters: An Efficient way to evaluate the performance of existing and proposed algorithms is to have segmentation evaluation measures. Evaluation criteria for segmentation can be divided into methods based on boundaries and regions [10].The following are two performance parameters used to evaluate the image segmentation.

The Rand index (RI): It is a quantity of the resemblance among two clusters. Known a set of 'n' factors also two partitions of 'S' to evaluate, it illustrates the below variables

'a' represents the amount of pairs of factors in 'S' in 'X' and in 'Y' in the similar set.

'b' represents amount of pairs of factors in 'S' which in 'X' and 'Y' are in dissimilar sets.

'c' represents amount of pairs of factors in 'S' which are in the similar set in 'X' and in dissimilar sets in 'Y'.

'd' represents amount of pairs of factors in 'S' which are in dissimilar sets in 'X' and in the similar set in Y.

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The Rand index RI is defined as,

$$\text{RI} = \frac{a+b}{a+b+c+d} = \frac{a+b}{\binom{n}{2}}$$

From the above equation, agreement numbers among X and Y is denoted as 'a + b' and disagreement numbers among X and Y is denoted as 'c + d. The RI have a value among '0' and '1', here '0' represents the two clusters which are not coincide on some pair of points as well as '1' represents clusters which are accurately the similar.

Global Consistency Error (GCE): It estimates the degree to which segmentation approach can be seen as an improvement of the other. Segmentations, which are connected, are viewed to be reliable, since they could stand for the same image segmented at various levels. Segmentation is a division of the pixels of an image into sets. The segments are groups of pixels. In the event that one section is an appropriate subset of the other, at that point, the pixel lies in a zone of modification, and the mistake ought to be zero. In the event that there is no Subset relationship, at that point the two areas covers in a conflicting way [11]. The formula for GCE is as per the following,

$$\text{GCE} = \frac{1}{n} min\{\sum_i (S1, S2, pi), \sum_i E(S2. S1. pi)\}$$

Wherever segmentation error measure obtains two segmentations 'S1' and 'S2' as input, also generates a real esteemed outcome in the range [0::1] where zero denotes no mistake i.e. error. For a given pixel, 'pi' consist segments in 'S1' as well as 'S2', which contain that pixel.

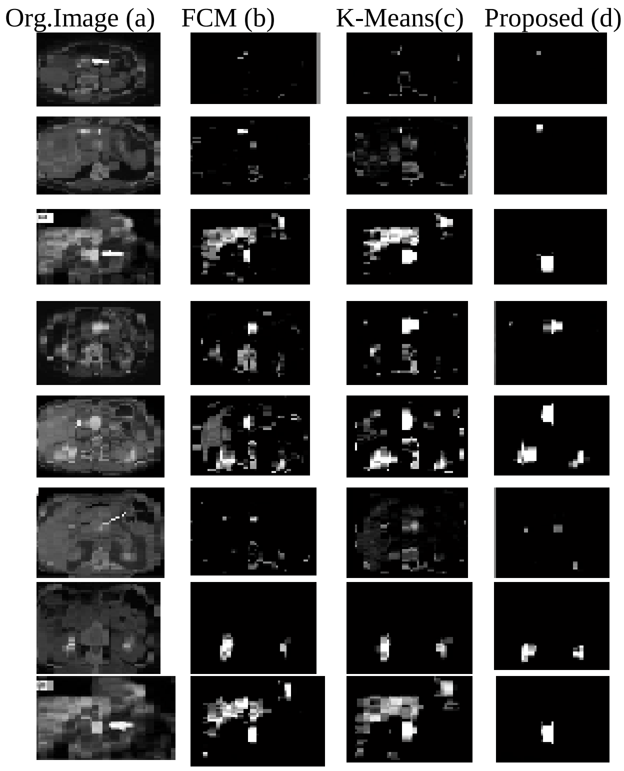
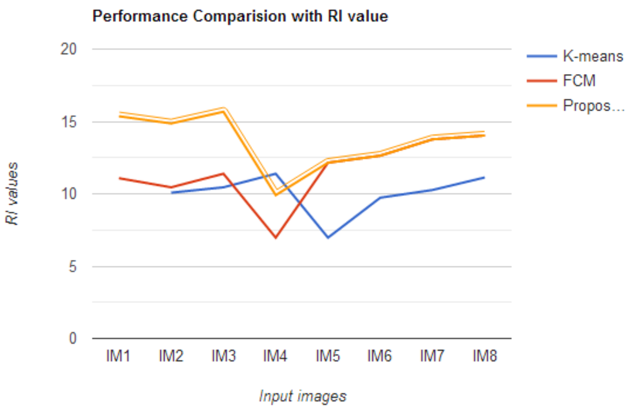


Fig 4. Results of segmentation on PET/CT pancreatic tumor images with various methods

It is found from the above results that the proposed method outperforms the procedures of segmentation without losing useful information such as edges and textures. In Figure 4, (a) represents the original image, (b) represents the FCM image, (c) represents the K-Means image, and (d) represents our proposed method.

From these figures, it is evident that the images segmented above using our proposed method have better visual quality than using other cluster-based filters.



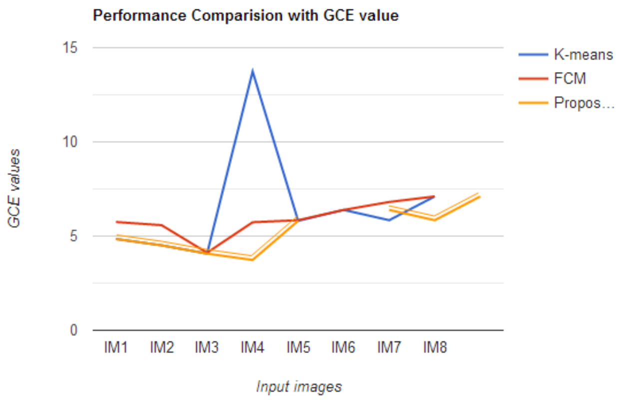


Fig5. Performance elevation metrics for K-Means, FCM and Proposed techniques.

Existing method fails to segment the exact pancreatic tumor region in PET/CT images. Since From the experimental results of segmentation, it is shown that proposed method gives the better performance in terms of accuracy over the other segmentation algorithms

V. CONCLUSION

The manner of proposed research work comprises of Image segmentation utilizing K-Means clustering plus Saliency map method. Salient map segmentation explores ways to distinguish salient objects from the background in input medical images. This method tries to imitate the Human Visual System, by using image features like contrast as well as spatial locations priors, to split salient objects. This paper establishes a novel approach to superior separate salient objects by incorporating inventive features comprising k-means clustering along with Saliency Map method. Clustering the saliency object prototype vectors instead of directly clustering the data is an effectual method. The experimental results illustrates that the proposed method proves the better performance than other segmentation techniques.

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