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A New Approach of Image Segmentation Method Using K-Means and Kernel Based Subtractive Clustering Methods

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Abstract

Image segmentation is considered as the first step in the image processing and therefore, a better segmentation will make it easier to analyse in the subsequent image processing steps. Clustering is commonly used image segmentation techniques because of its simple and fast algorithm. The quality of the segmentation of the clustering techniques are highly depends on the initial cluster centroid. Therefore, finding the optimal value of the centroid is an important task in the clustering techniques. In this paper, we have introduced a new image segmentation techniques which are based on the kernel-subtractive and k-means clustering algorithm. The kernel function is applied in the subtractive algorithm to find the cluster centroid and this centroids are used in the K-means clustering algorithm. The performance of the segmentation output are compared using RMSE and PSNR values and it validate the effectiveness of the proposed method.

Keywords: Image segmentation, Clustering Algorithm, k-means clustering, Subtractive clustering, Kernel algorithm.

INTRODUCTION

Image segmentation has been considered as first step for image processing. An efficient segmentation output make it easier in the next steps of the image processing. Therefore, many methods of image segmentation have been already proposed [1-4]. Clustering is one of the commonly and widely used image segmentation approached because of its simplicity and efficiency. There are different clustering algorithm like k-means, fuzzy c-means, spectral clustering, expectation and maximization etc. [5-9]. These different clustering approaches are proposed from different perspectives and are designed for different purposes. But existing clustering algorithm do require user-specified parameters as input. And the clustering performances depends highly on these user-specific parameters. One example of such parameter is the number of cluster, which is required by many clustering algorithms, e.g. k-means, fuzzy c-means etc. But there are some other algorithms which can be obtained the number of cluster by themselves, e.g. Subtractive clustering, DBSCAN etc. However, they also required other parameters to define as input. In Subtractive clustering, cluster radius and hypersphere radius need to define as input. In DBSCAN, it needs neighborhood radius and the minimum number of data.

Many methods have been proposed to determine these user-specific parameters. Many authors proposed some methods to determine the number of cluster and some other authors proposed methods to determine the cluster centroid and so on [10-15]. Therefore, many researchers are trying to propose different methods to solve the different problems of the clustering algorithm. Recently many works on the automatic image segmentation have been proposed. Chih-Chin and Chuan-Yu Chang [16] proposed a hierarchical evolutionary algorithm. It automatically segments the image and can be view as a variant of the traditional genetic algorithm. Haiyang Li, Hongzhou He and Yongge Wen [17] proposed a new hybrid method of dynamic particle swarm optimization and k-means. Yong Shi, Zhensong Chen, Zhiquan, Fan Meng and Limeng Cui proposed [18] a novel clustering based image segmentation known as ICDP algorithm which is based on the density peak algorithm. They have used the variants of integral channel feature along with the clustering method to find the density. Dongxia Chang, Yao Zhao, Lian Liu and Changwen Zheng [19] introduced a dynamic niching clustering algorithm which is based on the individual connectedness. It automatically calculates the optimal number of cluster and the cluster center using the adaptive selection of the compact k-distance neighborhood algorithm. Jian Hou, Huijum Gao and Xuelong Li [20] proposed a parameter independent clustering algorithm. They have used the Dominant Set to determine the input parameters of the DBSCAN clustering algorithm. Although there have been so many improved methods, these methods are either complicated or only some of the problems are overcome. Further studies are necessary to solve these problems of user-specific as input, especially the depending of the number of cluster and the initial centroids. Therefore the clustering algorithm with the automatic determination of parameters is still an open problem.

METHODS

The k-means algorithm is the powerful clustering algorithm but it still need the initialization of the centroid. Thus, in the proposed method the kernel based approach subtractive clustering algorithm is used to find the centroid of the clusters. Therefore, we have briefly discussed the k-mean algorithm, the subtractive algorithm and the kernel approach algorithm.

K-means Algorithm

K-means clustering algorithm is most commonly used clustering algorithms because of the simplicity and fast computation. It groups a collection of data into a k number group of data [21-23]. The pixel and the centroids are the two important parameters which defined a cluster. It is can be defined as an iterative algorithm in which it tries to minimizes the sum of distances from each object to its cluster centroid, over all clusters. Let us consider an image and number of cluster is defined as k. Let P(x) be the input pixels to be clustered and c be the cluster centroid. The algorithm for k-means clustering is given below:

1. Initialize the number of cluster k and the centroid for each cluster.
2. For each pixel of an image, calculate the Euclidean distance d can be calculated as:

$$d = \| p(x) - c_k \| \tag{1}$$

where p (x) is x^{th} input pixel of the image, c_k is the center for k^{th} cluster.

3. Assign all the pixels to the nearest centroid based on the distance d.
4. After all the pixels have been assigned, a new position of the centroid are calculated using the relation given below.

$$c_k = \frac{1}{k}\sum_{y\in c_k}\sum_{x\in c_k} p(x) \tag{2}$$

5. Repeat the process until it satisfies the tolerance value or error value.

Although k-means has many advantages of being easy to implement and fast computation, it do has some drawbacks. The quality of the final clustering results of the k-means algorithm highly depends on the initial selection of initial centroid and number of cluster.

Subtractive Clustering Algorithm

Subtractive clustering is also one of the commonly used clustering method which is based on the density of surrounding data points [24-25]. This method is the extension of Mountain clustering algorithm. One disadvantage of Mountain Clustering method is that with the increase in the dimension of data, its computation complexity grows exponentially. This problem is solved by Subtractive algorithm by using the pixels as the candidates for cluster center and therefore, the computation of this method is proportional to the problem size. Let P(x) be the pixel values of an image where, P(x,y)= {x_1, x_2, x_3…x_n}. Then each pixel is considered as a potential cluster centroid. The potential of a pixel's x_n is defined as:

$$P_n = \sum_{i=1}^{n} e^{\frac{-4\|x_n - x_i\|^2}{r_a^2}} \tag{3}$$

Where r_a is hyper-sphere cluster radius in pixel values space and it should be a positive constant. It can be defined as a value which is used to define the neighborhood around a pixel value. The symbol ‖*‖ denotes the Euclidean distance to define the distance between pixel values. After finding the potential of each pixel value, the pixel value with the maximum potential has been selected as the first cluster centroid. Let say, x_1 and p_1 as the first cluster centroid and its corresponding potential respectively. Then the potential of each pixel value is revised using the formula given below.

$$p_n = p_n - p_1 e^{\frac{-4\|x_n - x_i\|^2}{r_b^2}} \tag{4}$$

r_b is the hyper-sphere penalty radius and it should be a positive constant. From each pixel value, p_1 has been subtracted which are defined as a function of distance from the first cluster centroid. The pixel values which are near the first cluster centroid will be greatly reduced potential, and therefore the pixel values which are near the first cluster centroid will have less chance to be selected as the next cluster centroid. After calculating the revised potential of each pixel values, the pixel value corresponding to the next highest potential will be defined as the next cluster centroid. Thus, these processes will continues until a sufficient number of cluster centroid are obtained. The performance of the output image depends on values of the hyper-sphere cluster radius and the hyper-sphere penalty radius.

Kernel based approach

The main characteristic of the kernel approach is to map the data from input space into a higher dimension spaces and the data in the higher dimensional could become more easily separable [26-27]. Therefore, the kernel function is used in the subtractive clustering algorithm to increase the accuracy of the conventional subtractive clustering by exploiting a kernel function in calculating the potential of each data point. Thus, the potential calculated using the kernel function in a high dimensional space are much more informative than those of the conventional subtractive method calculated in the original space.

The kernel function can be defined as an inner product in feature space and therefore, the inner product between the data points are replaced with the kernel function. Let us consider the data points as X={x_1,x_2,x_3…x_n} in the dimensional space I, where n is the total number of data points and let us consider ϕ as non-linear mapping function from this input space I to a high dimensional feature space K. The dot product (x_i.x_j) in the input space is mapped to ϕ(x_i).ϕ(x_j) in the feature space by applying the non-linear mapping function. Mathematically, the kernel function can be expressed as:

$$k(x_i x_j) = \phi(x_i) \,.\, \phi(x_j) \tag{5}$$

There are different types of kernel function. But we have used Gaussian kernel function, which one of the commonly used kernel function. It can be expressed as:

$$k(x_i x_j) = \exp\left(-\frac{||x_i - x_j||^2}{2\sigma^2}\right), \text{ where } \sigma>0 \tag{6}$$

Proposed Method

Let us considered X={x_1,x_2,x_3….,x_n} be the pixel values of the input image and a non-linear mapping ϕ: I⟶ K. The potential function of each pixel x_i is defined as:

$$\mathrm{P}(x_i) = \sum_{j=1}^{n} \mathrm{e}^{\frac{-4\|\phi(x_i)-\phi(x_j)\|^2}{\mathrm{r_a^2}}} \tag{7}$$

Where $\|\phi(x_i) - \phi(x_j)\|^2$ is the square distance between $\phi(x_i)$ and $\phi(x_j)$ and this distance in the feature space is calculated as follows:

$$\|\phi(x_i) - \phi(x_j)\|^2 = \left(\phi(x_i) - \phi(x_j)\right).\left(\phi(x_i) - \phi(x_j)\right)$$
$$= \phi(x_i).\phi(x_i) - 2\phi(x_i)\phi(x_j) + \phi(x_{ij})\phi(x_j)$$
$$= K(x_i, x_i) - 2K(x_i, x_j) + k(x_j, x_j) \tag{8}$$

Therefore, the equation 7 can be rewritten as:

$$\mathrm{P}(x_i) = \sum_{j=1}^{n} \mathrm{e}^{\frac{-4(K(x_i,x_i)-2K(x_i,x_j)+k(x_j,x_j))}{\mathrm{r_a^2}}} \tag{9}$$

The potential of each pixel are calculated using the equation 9 and the centroid are calculated similarly to the conventional subtractive method by finding the maximum potential P_1=max [P(x_i)] and the corresponding pixel as the first cluster centroid x_1. After finding the first cluster centroid, the potentials are revised using the relation given below:

$$p_n = p_n - p_1 \mathrm{e}^{\frac{-4\|\mathrm{x_n}-\mathrm{x_i}\|^2}{\mathrm{r_b^2}}}$$

$$= p_n - p_1 \mathrm{e}^{\frac{-4(K(x_i,x_i)-2K(x_i,x_j)+k(x_j,x_j))}{\mathrm{r_b^2}}} \tag{10}$$

After the potentials have been revised, the second cluster centroid has been defined by finding the maximum potential in the revised potential, P_2=max [p_n]. Similarly, these process will be repeated until k number of centroid have been defined.

Proposed Algorithm:

1. Load the image.
2. Initialize the number of cluster k and the values r_a and r_b.
3. Use equation (9) to calculate the potential for every pixel value of the image.
4. Find the maximum potential in step 3 and set that pixel as the first center cluster and its corresponding potential as maximum potential.
5. Use equation (10) to update the potential value of other remaining pixels based on the first cluster center.
6. Again find the maximum potential in the step 4 and the corresponding pixel as the second cluster centroid.
7. Repeat step 5 and 6 until it finds the k number of cluster.
8. Initialize the k number of the centroid in the k-means algorithm.
9. Find the Euclidean distance of each centroid from every pixel of the image using the relation (1).
10. Assign the pixel with minimum distance with respect to the centroid at its respective cluster of the centroid.
11. Recalculate the new center location by using the equation (2).
12. Repeat the steps 9-11, until it satisfies the tolerance or error value.
13. Reshape the cluster into image.

RESULTS

The proposed method is implemented in Matlab and for the experimental purpose, we have used Berkeley Database [28]. In the Subtractive clustering algorithm, the parameters r_a and r_b are need to give a priori values. These two parameters defines the neighborhood distance and therefore, optimum value of these values would yield a more efficient segmentation output. In other words, these two parameters have to be chosen very carefully. For the experimental purpose, we have taken the values as r_a=0.5 and r_b=1.2. The number of cluster is also important parameter which need to be initialized. But we have taken the number of cluster as 3 for all the images. Moreover, the segmentation method based on the clustering technique like k-means, fuzzy c-means (FCM), Institutional fuzzy c-means (IFCM), Expectation maximization (EM), Subtractive algorithms have been used for comparing with the proposed method. The proposed method and the other clustering based image segmentation method are implemented in MATLAB and the output of the segmentation are shown in the figure 1. However, for the quantitative analysis the performance of the segmentation is usually analyze using different validate indexes [29-30]. In this paper, we have used RMSE and PSNR evaluation indexes to analyze the performance of the proposed method.

Root Mean Square Error (RMSE): It is considered as a standard performance measurement of the output image. It defines how much the output image has deviated from the input image. A smaller value of RMSE defined that the image is of good quality.

$$RMSE = \sqrt{\frac{1}{n_x n_y}\,\frac{\sum_0^{n_x-1}\sum_0^{n_y-1}\left[\left(r(x,y)\right)\right]^2}{\sum_0^{n_x-1}\sum_0^{n_y-1}[r(x,y)-t(x,y)]^2}} \qquad (11)$$

Peak to Signal Noise Ratio (PSNR): It can be defined as the ratio is the proportion between maximum attainable powers and the corrupting noise that influence likeness of the images. It measures the quality of the output image. A smaller value of PSNR means that the output image has poor quality. In the relation, r(x, y) is the input image and t(x, y) is the segmented image.

$$PSNR = 10.\log_{10}\left[\frac{max(r(x,y))^2}{\sqrt{\frac{1}{n_x n_y}\,\frac{\sum_0^{n_x-1}\sum_0^{n_y-1}\left[\left(r(x,y)\right)\right]^2}{\sum_0^{n_x-1}\sum_0^{n_y-1}[r(x,y)-t(x,y)]^2}}}\right] \qquad (12)$$

From the table 1, we can be observed that the proposed method have the smallest value of RMSE and figure 2 shows the graph plot of the RMSE values. Since RMSE measures the deviation between the images, the lowest value means less deviation. From the graph, it is clearly shown that the proposed method outperform the other methods. Similarly, figure 3 shows the graph plot of PSNR values and it measures the likeliness between the images. As we observed, the proposed method have highest PSNR value in all the images. Thus, these have proved the effectiveness of the proposed method.

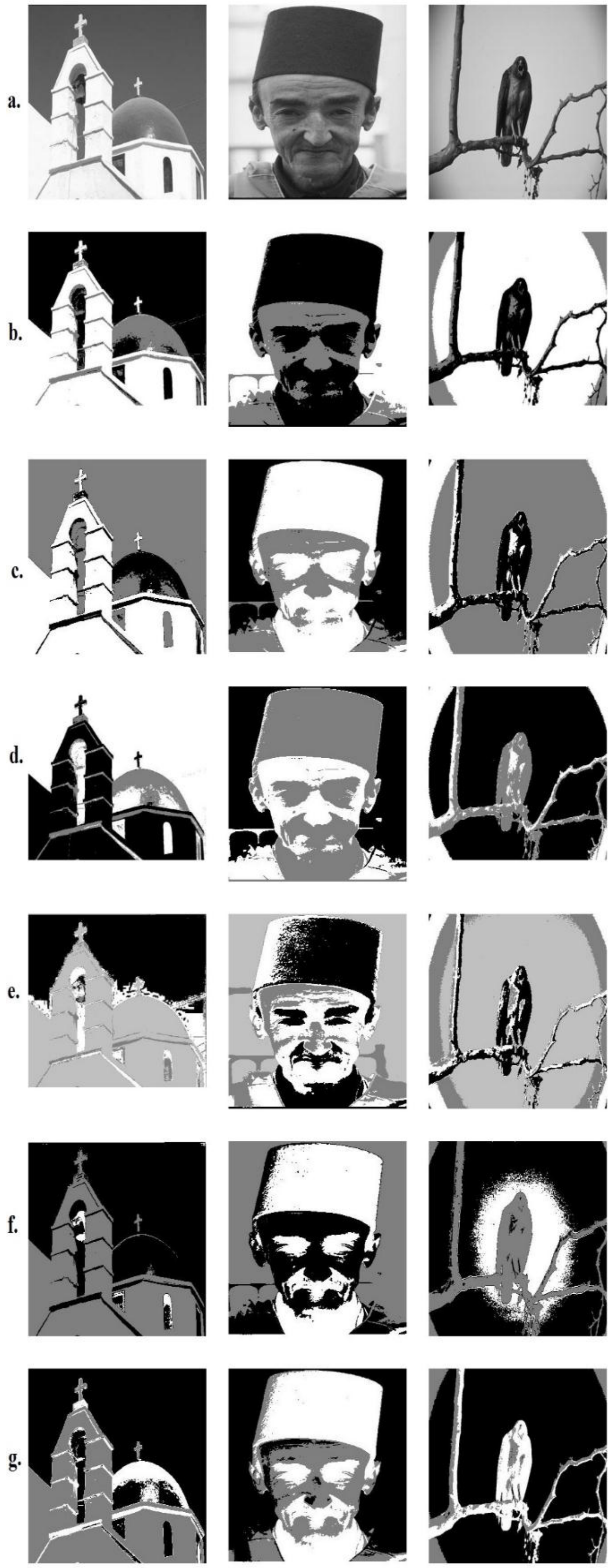

Figure 1: (a) Original Images, (b) K-means, (c) FCM, (d) IFCM, (e) EM, (f) Subtractive, (g) Proposed Method

Table 1: Comparison of the proposed method with different clustering algorithms.

Image	*Methods*	*RMSE*	*PSNR*
Church	K-means	0.0064	70.01
	FCM	0.0073	69.48
	IFCM	0.0048	71.32
	EM	0.0051	70.99
	Subtractive	0.0310	63.22
	Proposed	**0.0030**	**73.30**
Man	K-means	0.0079	69.03
	FCM	0.0419	70.09
	IFCM	0.0056	70.99
	EM	0.0049	71.22
	Subtractive	0.0346	62.60
	Proposed	**0.0044**	**71.69**
Owl	K-means	0.0079	68.75
	FCM	0.0070	69.03
	IFCM	0.0031	71.34
	EM	0.0094	67.74
	Subtractive	0.0401	61.46
	Proposed	**0.0032**	**72.38**

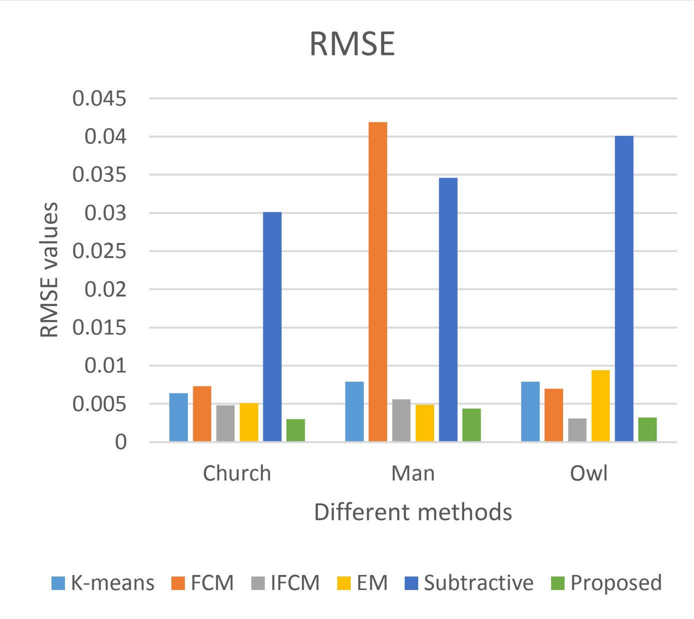

Figure 2: Plot for RMSE Comparison

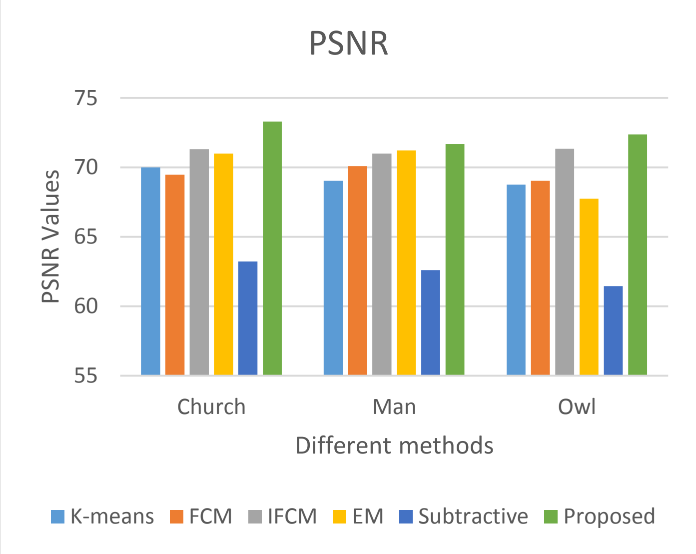

Figure 3: PSNR Plot Comparison

CONCLUSION

In this paper, a new image segmentation method is proposed based on the k-means and kernel based subtractive methods. The used of the kernel function in the conventional subtractive algorithm increases the efficiency of the conventional subtractive algorithm by transforming the input pixel space into a higher dimension, thus making the pixel values into more easily separable. Moreover, the proposed method is compared with the other clustering based image segmentation method using the evaluation indices, RMSE and PSNR values and it validated the effectiveness of the proposed method. Although the proposed method has yielded good performance indices, there is still some aspect that needs to be improved. In the future, we plan to use an optimization method to define the optimal value of the cluster radius and the hyper cluster radius. Besides, we can also use different and improved kernel function in the subtractive clustering.

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