A survey on Image Segmentation Methods using Clustering Techniques

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Abstract—Image segmentation has been considered as the first step in the image processing. An efficient segmentation result would make it easier for further analysis of image processing. However, there exits many algorithms and approaches for image segmentation. Clustering is one of the commonly used image segmentation techniques. In this paper, we have briefly describe some of the clustering techniques and discuss some of the recent works by researchers on these techniques.

Index Terms—Image segmentation, Clustering techniques, K-means, Fuzzy c-means, Subtractive, Expectation Maximization, DBSCAN.

I. INTRODUCTION

Image segmentation is a process of partitioning an image into a multiple number segments, so it is a method to classify the pixels of an image correctly in a decision oriented application. Therefore, we can state that the objective of image segmentation is to simplify or change the representation of an image or convert the information of an image into a more meaningful form so that it make it easier for further analysis. It divides an image into a number of specific regions such that the pixels exhibits high similarity in each regions and between the regions they have high contrast. It is a valuable tool in many fields and applicable in many application like health care, medical image processing, traffic image, pattern recognition etc. There are different techniques and approaches for image segmentation like threshold based, graph based, and morphological base, edged based, clustering based, neural network based etc.[1-3] All these methods have their own advantages and disadvantages and therefore, one have to choose the algorithm based on the needs from their own perspective. From these techniques, one of the most used efficient method is clustering method. Again, clustering techniques [4-7] can be divided into different types like K-means clustering, Fuzzy C-means clustering, Subtractive clustering methods etc. In this paper, we will briefly discussed the different methods of the clustering techniques and some of the recent works on these techniques.

A. Segmentation Techniques

There are many methods for segmenting an image that have been recognized by scientists and researchers. Therefore, there are several such techniques that are quite popular, important and are regularly used for image segmentation. These are classified as follows:

1. Thresholding based segmentation
2. Region based segmentation
   a. Region growing
   b. Region merging and splitting
3. Edge based segmentation
4. Clustering based segmentation
5. Bayesian based segmentation
6. Classification based segmentation

Threshold: Thresholding is the simplest image segmentation method. It tries to differentiate between the image background and image foreground. A thresholding procedure uses the intensity histogram and attempts to determine the intensity values called threshold value and these threshold values differentiate the desired classes. So it segment the image based on the threshold value and hence it is fast and computationally efficient method. Although it is simple and fast, it does not take into account the spatial characteristic of an image. So thresholding method is sensitive to noise and intensity inhomogeneity.

Region Growing: Region growing is a method for extracting a connected regions of the image which consists of group of pixels with similar intensities. In this method, a point is initially defined which is known as seed point. Then all the points which are connected to seed point having same intensity as that of seed point are selected and are added to the growing regions. This procedure is repeated until no more pixel can been added to the region.

Region Splitting: Rather than choosing initial seed as in case of region growing, image can be divided into unconnected regions and then merge again based on some condition. That means it consists of two steps- splitting and merging step. Quad tree method is generally used in splitting.

Clustering: Clustering method is an unsupervised image segmentation method. It classify the image into a finite number of cluster, where the number of cluster can be user defined or can be find using an algorithm. So in this process there is no training stages, but train themselves using the available data. Based on some criteria, the pixels are grouped together and form the cluster. Initialization of values are required and these initializations plays an important role in determining the performance of the...
segmentation. So initialization should be done very carefully.

**Edge Detection:** Edge detection method detects the edge or pixels between different regions. The condition for different regions may be rapid transition of intensity. So those pixels are extracted and linked together to form a closed boundary.

**Bayesian:** Bayesian method is used for the classification purpose and it is works by considering probability in the image to construct models based on the probability that is further utilized for the class assignment of pixels in the image. There are different approaches in Bayesian method like Markov Random Field (MRF), Expectation Maximization (EM).

**Classification:** Classification method use data with known labels to partition the image feature space. In other word, classification of image done by deriving a feature space from the image. Then this feature space is further divided into different regions depending upon the function being defined in the feature space. This classification method can be both supervised and unsupervised. In supervised, the image is trained and it is manually segmented and it is used further for the automatic segmentation of new images.

II. CLUSTERING ALGORITHM

In this chapter we will discussed about different techniques of clustering methods. We can define the clustering as the classification of objects into different clusters. In other words, it can be considered as the partition of data set into subsets, in such a way that the data in each subset should exhibit some common properties. The properties can be proximity according to some defined distance measure or other means of measure. There are many clustering methods such as hard clustering or fuzzy clustering, each of which has its own advantages.

A. K-means Algorithm

K-means clustering algorithm is one of the most commonly used clustering algorithms. In k-means clustering, it partitions a set of data into a k number group of data [8-9]. Each cluster in the partition is defined by its data member and by its cluster centroid. The centroid can be defined as the point in which the sum of distances from all the objects in that cluster is minimized. Therefore, K-means is an iterative algorithm in such a way that it minimizes the sum of distances from each object to its cluster centroid, over all clusters.

Let us consider an image having a resolution of x*y and the number of cluster is defined as k. Let p(x,y) be the pixels of the input image and c as the cluster centers. The algorithm for k-means clustering is as follow:

1. Initialize the number of cluster k and centroid of each cluster.
2. For every pixel of an image, calculate the Euclidean distance d using the relation given below.

\[ d = \| p(x, y) - c_k \| \] (1)

where \( p(x, y) \) is the pixel at \((x, y)\)th of the input image, \( c_k \) is center for \( k\)th cluster.
3. Assign all the pixels to the nearest center based on Euclidean distance \( d \).
4. After all pixels have been assigned, the new position of the center has been recalculate using the relation given below.

\[ c_k = \frac{1}{k} \sum_{y \in c_k} \sum_{x \in c_k} p(x, y) \] (2)

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

Although k-means is easy to implement and it has advantages, it still has some drawbacks. The quality of the final segmentation results of the k-means algorithm is highly depends on the initial selection of initial centroid of the clusters. Many algorithm have been proposed to overcome these drawbacks. Haiyang Li [10] et al. proposed a new hybrid method of dynamic particle swarm optimization (DPSO) and k-means. DPSO finds the optimal solution for k-means and this optimal solution are fed into the k-means. So in this algorithm, k-means is no longer dependent on the number of initial cluster. Again, R. Jens et al. and G. Wiselin Ji [11] proposed a hybrid method of k-means with the optimization method flower pollination algorithm. They used Flower pollination algorithm to avoid trapping of k-means algorithm in local optimum algorithm. Samir Brahim Belhaouari, Shahnawaz Ahmed and Samer Mansour [12] introduce a new method of optimization method of K-means. They used the method of localization by reshaping the input image into vector and then the optimized k-means algorithm is applied twice to cluster the image pixels into one class. Sina Khanmohammadi et al. [13] proposed a new and improved k-means clustering algorithm knows as overlapping k-means (OKM). They also introduced hybrid method of the k-harmonic means and overlapping k-means algorithm (KHM-OKM). The output of the KHM method is used to initialize the cluster center of the OKM algorithm.

B. Fuzzy c-means algorithm

Fuzzy c-means algorithm is one of the methods which is used to classify the given set of data into a different similar group [14-15]. So pixel value of an image can belong to more than one cluster. For every pixel of image, there exists a value called membership value for each cluster, which defines the degree of share of that particular point in each cluster. So membership matrix is a matrix consisting of membership value of each pixel for all
clusters. In other word, it forms segmentation through fuzzy pixel classification in the sense that pixels are allowed to be in multiple classes with degree of membership between 0 and 1. Let us consider a finite set of \( n \) number of data \( X=\{x_1, x_2, \ldots, x_n\} \). Fuzzy c-means algorithm divides the data set \( X \) into a group of \( c \) fuzzy cluster based on some specified condition. It is an iterative process which is based on minimization of the objective function. The objective function is given below.

\[
J_m = \sum_{i=1}^{n} \sum_{j=1}^{c} u_{ij}^m ||x_i - c_j||^2
\]  

(3)

Here \( m \) is fuzzification parameter which determines the degree of fuzziness in the clusters, \( u_{ij} \) is the degree of membership of \( x_i \) in the cluster \( j \), \( x_i \) is \( i^{th} \) data points and \( c \) is \( j^{th} \) cluster center, and \( ||*|| \) is the Euclidean distance. For each iteration, it tries to minimize the cost function while changing the value of degree of membership of each data point. The algorithm for Fuzzy c-means algorithm is given below.

1. Initialize number of cluster and membership function matrix \( u \).
2. Find value of center for each cluster using the formula given below.
   \[
   C_j = \frac{\sum_{i=1}^{n} u_{ij}^m x_i}{\sum_{j=1}^{c} u_{ij}^m}
   \]
   (4)
   3. Calculate the error or cost function, and check weather if it is lower than the given specific threshold value or improvement over previous iteration.
   4. If it is satisfy than it will cluster the data.
   5. If it is not satisfied, then update the membership matrix using the relation given below and continue the algorithm again.
   \[
u_{ij} = \frac{1}{\sum_{j=1}^{c} \frac{|x_i - c_j|^2}{|x_i - c_j|^2}} \]
   (5)

Intuitionistic Fuzzy c-means:

This algorithm is the modification of conventional Fuzzy c-means algorithm [16]. The objective function of the conventional Fuzzy c-means is modified to a new objective function which is known as intuitionistic objective function. So it tries to minimize the new objective function which is given below.

\[
J_{IFCM} = \sum_{i=1}^{c} \sum_{k=1}^{n} u_{ik}^m d_{ik}^2 + \sum_{i=1}^{c} \pi_i (1 - \pi_i)
\]

(6)

When \( m=2 \), \( u_{ik} = u_{ik} + \pi_{ik} \), where \( u_{ik} \) denotes the intuitionistic fuzzy membership of \( k^{th} \) data in \( i^{th} \) class. \( \pi_{ik} \) is known as hesitation degree which is given below.

\[
\pi_{ik} = 1 - u_{ik} - (1 - u_{ik}^n)^{1/a}
\]

(7)

And

\[
\pi^*_i = \frac{1}{n} \sum_{k=1}^{n} \pi_{ik}
\]

(8)

The second term in the objective function is known as intuitionistic fuzzy entropy (IFE), and it is introduced to maximize the good points in the cluster. So the goal here is to minimize the entropy of the histogram of an image. Then the modified cluster center from the conventional Fuzzy c-means is given below.

\[
c^*_i = \frac{\sum_{k=1}^{n} u_{ik}^m x_k}{\sum_{k=1}^{n} u_{ik}^m}
\]

(9)

The cluster center and membership matrix are updated in each iteration and the algorithm stops when maximum difference in change of membership value is less than a threshold value.

**Type-2 Fuzzy c-means:**

It is a modified method of conventional fuzzy c-means algorithm [17]. It tries to converge cluster center in more desirable location even in the presence of noise. In this algorithm, the higher membership value should contribute more than the membership value which is smaller, when updating the cluster center. The modified membership value of type-2 fuzzy c-means is given below.

\[
a_{ip} = u_{ip} - \frac{1}{2} - u_{ip}
\]

(10)

Where \( a_{ip} \) and \( u_{ip} \) are the membership value of type-2 and conventional fuzzy c-means algorithm respectively. And the updated center are given by substituting the modified membership value in the conventional cluster center formula.

\[
c_i = \frac{\sum_{k=1}^{n} a_{ik}^m x_k}{\sum_{k=1}^{n} a_{ik}^m}
\]

(11)

The cluster center \( c_i \) and membership matrix \( a_{ip} \) are updated in each iteration and the algorithm stops when maximum difference in change of membership value is less than a threshold value. In FCM, the result depends heavily on the input parameters e.g. number of cluster, membership function. Many authors proposed different methods to solve this problem. Li Ma et al. [18] proposed a new hybrid method of artificial fish swarm algorithm with FCM. This method solve the problem of depending on initial clusters, falling into local optimal solution and sensitivity to noise disturbance in FCM algorithm. Some authors proposed improved method of FCM by optimizing the parameters of FCM. Many have used optimization method like Genetic algorithm, Particle swarm optimization etc. Yogita K et al. [19] proposed an improved FCM algorithm. They have analyzed the various function of FCM by modifying the standard fuzzy objective function and by updating the fuzzy membership function and cluster center. E.A. Zanaty [20] have introduced a new method for determining the number of cluster by using the kernelized fuzzy c-means algorithm. They have used Gaussian radial basis function basis function classifier (GRBF) in the Euclidean distance in FCM. An-Xin Ye and Yong-Xian Jin et al. [21] proposed an improved Fuzzy c-means algorithm by using the improved quantum Genetic algorithm. They have used the quantum bits encoding with real number techniques to encode the chromosomes in the Genetic algorithm. Again the chromosomes are renovated by quantum rotating gates and mutated by quantum hadamard gate.
C. Subtractive Algorithm

Subtractive clustering is one of the commonly used clustering technique. It can be defined as a method based on the density of surrounding data points to find the optimal data point to define a cluster centroid [22-23]. This method can be considered as the expansion of Mountain method. The main disadvantages of Mountain clustering is that, with the increase in the dimension of data, its computation complexity grows exponentially. Therefore, the problems associated with the mountain clustering has been solved by using the Subtractive Clustering.

Consider n number of data points: \( X = \{x_1, x_2, x_3, \ldots x_n\} \).

According to the subtractive clustering algorithm, each point is considered as a potential cluster center. The potential of each data point’s \( x_n \) is defined as:

\[
P_n = \sum_{i=1}^{n} e^{-\frac{4|\|x_n-x_i\|\|^2}{r_a^2}} \quad (12)
\]

Where \( r_a \) is hyper sphere cluster radius in data space. It should a positive constant and it defines the radius of the neighborhoods. The symbol \( |\| \cdot \|\| \) is the Euclidean distance. So the measure of the potential of the data point can be considered as a measure of function of distance to all other data points. After finding the potential of each data points, the data point with maximum potential are declare as the first cluster center. Now, consider \( x_1 \) and \( p_1 \) as first cluster center and its corresponding potential respectively. Then the potential of each data point has been revised using the formula given below.

\[
P_n = p_n - p_1 e^{-\frac{4|\|x_n-x_1\|\|^2}{r_b^2}} \quad (13)
\]

\( r_b \) is the hyper sphere penalty radius in data space. The value of hyper sphere should a positive constant. From the first cluster center, an amount of potential has been subtracted from each data point. Therefore, the data points near the first cluster center will have greatly reduced potential, and thus it have less chance to be selected as the next cluster center. After the revise potential of each data points has been calculated, the next highest potential is declared as the next cluster center. Until k-number or sufficient number of cluster is generated, repeat the process. The result of the cluster are highly depended on values of the hyper sphere cluster radius and the hyper sphere penalty radius.

Some of the recent works which have been already done are presented here. Gokham Bilgin, Sarp Erturk and Tulay Yildirim [24] used a new subtractive clustering based on the similarity segmentation and used one-class support vector machine (OC-SVM) as a validation method. Mariam El-Tarahily [25] et al. proposed a new optimized subtractive clustering technique using the Particle Swarm Optimization technique. They used the subtractive clustering technique to find the number of cluster and the centroid of the cluster and these values are used in the particle swarm optimization technique. Abdul Haris Rangkuti [26] et al. introduced a hybrid method of Subtractive clustering and Fuzzy c-means clustering. They used subtractive method to find the number of cluster and centroid of the cluster. The cluster centroid are used in the fuzzy c-means to find the membership function.

D. Expectation and Maximization

Expectation and Maximization (EM) is one of commonly used clustering based image segmentation method [27-28]. It is density based unsupervised method where it finds the maximum likelihood estimate of the parameters from a given data set. The EM algorithm consists of two step [29]. In expectation process, the expectation of likelihood of probability function \( p(C_k/x_{i,j}) \) is calculated, where \( p(C_k/x_{i,j}) \) defines the probability of belonging of each pixel value \( x_{i,j} \) into a certain cluster \( C_k \). In maximization process, it calculates the maximum likelihood estimates of the parameters. After calculating the parameters, it have been used in expectation process and repeat the process until the result converges.

Mathematically for a given training dataset \( x \) and model \( p(x; z) \) where \( z \) is the latent variable, we have:

\[
I(\theta) = \sum_{i=1}^{m} \log p(x; \theta)
= \sum_{i=1}^{m} \log p(x, z; \theta) \quad (14)
\]

As we can observed in the above equation, the log likelihood is defined in terms of \( x \), \( z \) and \( \theta \). But since \( z \), the latent variable is unknown, we have use approximations values. These approximations take the form of Expectation and Maximization steps and formulated mathematically below.

E Step, for each i:

\[
Q_i(z^{(i)}) := p(z^{(i)}|x^{(i)}; \theta) \quad (15)
\]

M Step, for all z:

\[
\theta := \arg \max \sum Q_i(z^{(i)}) \log \frac{p(x^{(i)}|z^{(i)}, \theta)}{Q_i(z^{(i)})} \quad (16)
\]

where \( Q_i \) is the posterior distribution of \( z^{(i)} \)’s given the \( x^{(i)} \)’s.

Conceptually, the Expectation and Maximization algorithm can been defined as a variant of the K-Means algorithm where the membership of any given point to the clusters is not complete and can be fractional.

Chad Carson [30] et al. introduced a new approach of image segmentation using EM. Aristeidis Diplaros [31] et al. introduced a spatially constrained EM algorithm that iteratively maximize a lower bound on the data log-likelihood. It is same as the conventional EM algorithm except that the labels posterior are smoothed over pixels between each E- and M-steps by s standard filter. Mohamed Ali Mahjoun and Karim Katli [32] proposed a new EM algorithm based on the adaptive distance. They defined a new approached to define the new distance and the proposed distance thus permitted to get a new variant of the EM method that is adapted more.
E. DBSCAN

DBSCAN is one of the commonly used density based clustering algorithm [33]. It is based on the density of the pixels values. But its need a priori initialization of parameters like MinPts, Eps. Eps can be defined as neighborhood radius and MinPts is the minimum number of points in the neighborhoods. At first, a pixel is consider as a core pixel if it have at least MinPts points in its Eps neighborhood. If one non-core pixel is reachable from a core pixel, then it is declared as a border pixel. Otherwise, the non-core pixel will be considered as an outlier pixel or the pixel will be neglected. DBSCAN perform the clustering process in a sequential manner. For an unconsidered pixel p, DBSCAN collects all pixel in the Eps neighborhood of p. If p is a core pixel, then all the pixels in its Eps-neighborhood will be consider as in a cluster. For each pixel in the cluster, we find all the density-reachable pixels and add them into the cluster. Thus until no new density reachable pixel has been found, repeat the process. The algorithm for DBSCAN is given below:

2. Fetch all pixels that are density-reachable from p with respect to Eps and MinPts.
3. A cluster is formed, if p is a core pixel.
4. Repeat the process for remaining pixels, if p is a border pixel and none of the pixels are density reachable from p.
5. Repeat the above process until all of the points have been examined.

Different new and improved DBSCAN had been proposed by many authors. G. Chaudhari Chaitali [34] proposed new hybrid algorithm based on partitioning based DBSCAN and Ant clustering. It uses PD-based partitioning and PACA partitioning depends on the dimension of datasets. If the dataset is in 2D, then it uses PD-based partitioning method to partition the data otherwise, it uses PACA method. And for each partition, this algorithm constructs R*-tree, plots k-distance graph and runs DBSCAN. Mohameed T. H. Elbatta et al. [35] have proposed a new approach based on the varied density datasets analysis. Eps is an important parameter in DBSCAN and therefore, a dynamic method have been used to find the suitable value of Eps for each density level of the dataset. Nirmalya Chowdhury et al. [36] proposed a new improved DBSCAN algorithm by using the minimum spanning tree (MST) based objective. A threshold based on MST of data points of each cluster are generated which are used to remove noise from the final clustering. Jian Hou et al. [33] proposed a parameter independent clustering algorithm. They have used Dominant Set (DSet) to determine the input parameters of DBSCAN clustering algorithm. Thus merging the merits of DSets and DBSCAN, the proposed algorithm can do the clustering without any input parameters.

III. CONCLUSION

In this paper, image segmentation techniques based on the clustering techniques are briefly described. We have also discussed about the advantages and disadvantages of each methods. Moreover, we have observed that all the methods require a prior user initialization, which is the main drawback of the clustering techniques. Therefore, we have to choose the method carefully based on the availability of the data or based on the requirement of the user. Lastly, we have also cover some recent works on the clustering techniques.

REFERENCES


