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Segmentation of Images using Automatic Fuzzy Clustering Framework

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***Abstract*- Clustering is grouping up of data points. Using clustering algorithms, the data points can be grouped with similar properties. Fuzzy clustering is grouping of data points of clusters of one or more clusters. Density Peak (DP) clustering can find the clusters but when the sum of clusters is increased, it suffers memory overflow, because when a normal size image is used for image segmentation which contains a greater number of pixels, it results in a high degree of similarity matrix. To avoid this, Automatic Fuzzy Clustering Framework (AFCF) for segmentation of image could be introduced. This framework contributes in three ways. To begin with, the Density Peak method is used for the concept of Super Pixel, which decrements the similarity matrix size and there by enhances DP algorithm. Secondly, the Density Balance technique generates a stable decision graph, which enables the DP algorithm for a fully autonomous clustering. Lastly, to improve image segmentation outcomes, the system which works on prior entropy employs a Fuzzy c-means clustering. Through this, information of pixels in spatial neighbors are considered and can see improved segmentation results. In the present work, an attempt is made to develop and explain the segmentation of images using Automatic Fuzzy Clustering Framework.**

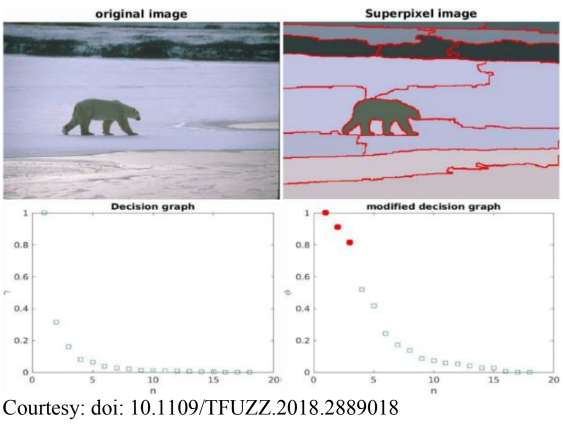
Keywords- Fuzzy Clustering, Density Peak, Image Segmentation, Super Pixel, Density Balance, Fuzzy C-means Clustering

I. INTRODUCTION

In the rapid growing technology days, it can be said that the clustering is the most important and useful tool these days for data mining and computer vision, where clustering basically means dividing and grouping of the objects of a dataset into a meaningful subclass. In the clustering there are many algorithms which are successful in data classification and also in image segmentation, but the task automatic clustering is a big challenge to achieve the most accurate results. Normally, the image segmentation algorithm which are based on clustering have various advantages. To embark upon, achieving the unsupervised segmentation of image without the labels and comparatively. Secondly, the various image segmentation algorithms which are based on bunching are more effective than the other algorithms used for segmentation of image because they take fewer parameters than the ones which are of clustering based. Some of the examples of other algorithms are region merging, active contour models and random walkers. Lastly, this method can be easily applied to the algorithms of clustering on multi channels for multi-dimensional data for the classification. Just like advantages clustering with image segmentation have disadvantages too as in clustering due to iterative optimization on the same pixels, it consumes a lot of time to generate the high-resolution images and also clustering is complex to the noise due to absence of the spatial surrounding information.

This fault is rectified by using the technique of merging local 3D spatial surrounding data to objective functions so that to accelerate the toughness of the algorithms. Like local fuzzy c-means clustering algorithm, with neighbor constraint deviation sparse fuzzy c-means and neighborhood weighted fuzzy c-means clustering algorithm, kernel metric and weighted fuzzy factor. With around two limitations such as these take more amount of period than the predictable c-means clustering algorithm due to its larger computational complexity and also as spatial neighboring has to be calculated for each iteration. Additionally, in color image segmentation the time complexity is worse than other algorithms. Another disadvantage in this algorithm is for each pixel of the image there are fixed neighboring window which results poor segmentation. So, to overcome this, an idea is that to include adaptive neighboring spatial information which accelerates the result accurately.

On the other hand, the second fault in these algorithms is the researchers have taken gray levels to perform the clustering on it as a replacement for pixels. So, to avoid the iterative distance calculations and also the pixels in the image are greater to the gray levels. Through avoiding the iterative distance computations which in results the decrease in execution time of the algorithms becoming enhanced fuzzy c-means (FCM) and faster generalized FCM algorithm [13], [16]. These algorithms achieve greater efficiency when histograms are merged with the objective functions. But these are limited to only the gray scale images as color images require more complex histogram [17] [18]. Here the new problem arises, in order to reduce the heavy computations while using the adaptive spatial neighbor information. One of the researchers selected super pixel algorithm to get adaptive information and at the same time to lessen the sum of clustering samples. The fuzzy double c-means clustering based on sparse self-representation, that stills tops in the higher computational complexity comparatively with the other algorithms. Based on the super pixel and enhanced fuzzy c-means clustering, researcher has proposed a super pixel based fast fuzzy c-means color segmentation algorithm [1], [2], [3]. It mainly consists of two advantages, firstly transform of watershed built on gradient reconstruction with multiscale reconstruction, stands very useful in the final stage of the clustering in the super pixel technology. Secondly, the color histogram is merged with the impartial function of the fizzy c-means clustering to speed up the algorithm [12], [15]. Fig. 1 shows the different stages involved in image segmentation [2].



Courtesy: doi: 10.1109/TFUZZ.2018.2889018

Fig.1. Various stages in segmentation of image

Algorithms such as the genetic algorithm, robust learning-based schema and eigenvector analysis were used normally by the researchers to automatically calculate the quantity of clusters. But algorithm was able to determine the quantity of clusters for the unlabeled data but failed in detecting the spatial information with respect to the final segmentation result [14], [20]. The density peak (DP) algorithm initially will identify the density peaks of the data and then calculates the shortest distance between the center point and the other midpoints that are having high local density in comparison to the main one, at last produces the decision-graph to achieve the faster clustering but in the decision graph it only provides the graph but does not provide number of clusters. So, the researchers have projected another algorithm to overcome the drawbacks in the density peak algorithm [2], [4]. This algorithm was able to overcome the draw backs of the density peak algorithm but still fails to in considering the spatial information. In the present paper an algorithm called AFCF for segmentation of images is proposed which is based on the super pixel, fuzzy clustering through prior entropy and density peak computation. Here the similarity matrix is ignored as it limits some of the features of the density peak algorithm in the image segmentation. Here the process goes which initially takes a super pixel algorithm then simplifies the considered picture, gets a minor similarity matrix that automatically rest on number of super pixels. So, the calculations will be performed based on those small matrixes to obtain the decision graph.

To attain automatic clustering algorithms there is requirement of work on the decision graph to get amount of clusters without the involvement of human automatically and at last prior entropy is merged into fuzzy c-means clustering to enhance the results. So, the following method consists of various advantages, AFCF is completely automatic clustering frame work for image division, but here the quantity of clusters is not a mandatory parameter and also automatic fuzzy clustering framework produces accurate amount of clusters and helps in achieving the better image segmentation results as it uses prior entropy and other spatial data of the images. Unlike other algorithms AFCF does not demands more memory which are linked to the DP algorithm.

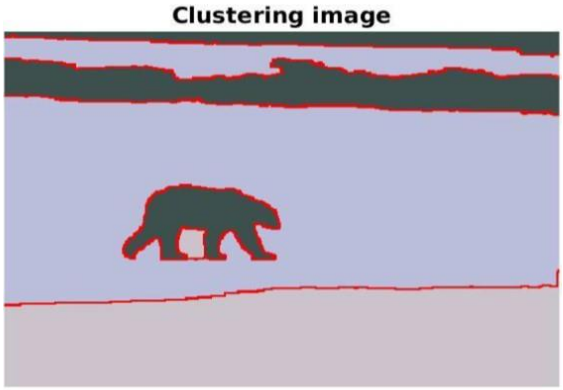
II. OBJECTIVES

Despite the fact that multiple clustering algorithms are successful in segmentation of image and data categorization in it is difficult to get automatic results. This is a challenging subject and image segmentation requires clustering and fine results. While clustering an image using various algorithms, the clustering should be done in such way that partial neighboring data shouldn't be ignored. It has many clustering algorithms for image segmentation, some algorithms will give correct number of clusters and some cannot. In some algorithms, it needs to set the clusters manually but the main problem here is the algorithms which give correct number of clusters will suffer memory overflow. The other challenge is while segmenting an image is, if it segments an image using any algorithm, first the image is clustered into various clusters. Here a greater number of clusters is observed than required which will create burden on memory. This needs to cluster an image such a way that the unwanted information in the image should not be considered.

III. LITERATURE REVIEW

Clustering always produces image segmentation results depending on number of clusters present. Despite the fact that there are a number of existing and adaptive clustering algorithms which can give approximate number of clusters automatically, they are complicated and inconvenient to use for segmentation of images. There are some methods to achieve automatic clustering like the robust learning-based schema, the eigenvector analysis, the inherited algorithm and the particle swarm optimization. Despite the fact that these methods can find the sum of clusters, they are unstable for clustering in unlabeled data collection and not suitable for segmentation of image because the spatial surrounding information is lost, resulting in a rough segmentation result. To achieve fast clustering, the density peak algorithm first detects the data of density peaks, then calculates the shortest distance between center and additional center with a high local density from the center and lastly plots a decision graph. The DP algorithm just gives a decision graph without any specification about the number of clusters. To avoid this, researcher proposed an improved and powerful automated algorithm to overcome the limited scope for density peak algorithm [7], [8]. Although this process could be achieved mechanically, the quantity of clusters gives higher experimental and practical results, it is still flawed for the reason that spatial data of photos is overlooked.

To achieve clustering automatically two issues must be solved in order to segment images. The first is to delete image data that is redundant. To use the DP algorithm, it needs a small similarity matrix. The second goal is to improve the DP algorithm in order to obtain more efficient results. For increasing the number of clusters and improve image segmentation, super pixel algorithms can be used to make the DP methodology easier to compute, then use a DP algorithm to discover the number of clusters and prior entropy enhances segmentation of image. Fig. 2 shows the final segmented image by implementation of AFCF [2].



Courtesy: doi: 10.1109/TFUZZ.2018.2889018

Fig.2. Final segmented image using AFCF

IV. METHODOLOGY

In this project, it is proposed automatic fuzzy clustering framework for segmentation of images which is stimulated using image super pixel. To generate a pre-segmentation result, AFCF uses a super pixel algorithm. Secondly, a decision-graph is generated using the DP algorithm on the image of super pixel. Because of the amount of area contributed in the super pixel image is substantially slighter than the amount of pixels in the source image. Density peak technique requires less memory and has lower complexity of computation. The density balancing approach is then utilized to create more efficient decision graph which outputs the quantity of clusters directly. Fig. 3 illustrates the different stages involved in image segmentation [2].

Courtesy: 10.1109/TFUZZ.2018.2889018

Fig.3. Segmentation of image using AFCF

The points in this graph are separated into groups by determining the maximal interval of neighboring points. The primary group of data points are referred to as cluster centers. Lastly, picture segmentation is achieved via prior entropy in fuzzy clustering [5], [6], [19]. Additionally, it is completely automatic for segmentation of image as the quantity of clusters is determined automatically which results in better results in image segmentation since it is employed by prior entropy and super pixel algorithms. AFCF is required to segment images that are synthetic and real, represent that its able to determine precise sum of clusters. This method has low memory consumption in the experimental environment and has less computational complexity as density peak algorithm is performed on super pixel image [21]. Fig. 4 illustrates the different steps in terms of the proposed project.

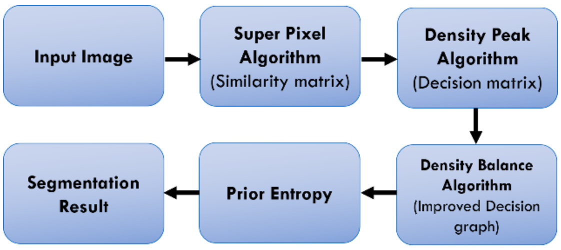


Fig.4. Flowchart of AFCF

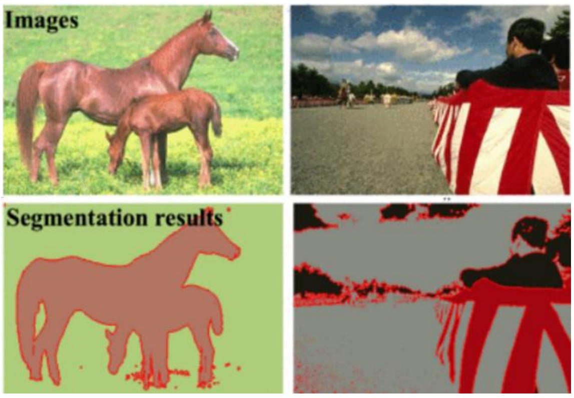
V. ADVANTAGES AND LIMITATIONS

The automatic fuzzy clustering framework doesn't depend on the sum of clusters. The increase in the sum of clusters doesn't affect the memory and computational complexities. This framework uses the spatial information of images and prior entropy. With this, the segmentation of the image will be effective and the clustering can be done more proficiently. Super pixel algorithm, density peak algorithm, density balance algorithm, and prior entropy are the building blocks of this framework that can be easily implemented and using these algorithms fast clustering of the images will be accomplished [9], [10], [22]. Instead of manually clustering the clusters and segmenting, it is done automatically in this framework which ensures fast clustering and segmentation of an image with low computational and memory capacity. The useless information or noise in the image could be clustered automatically which improves the analysis of the image. Better segmentation of the image and improved image processing results can be given as the output since the clustering framework is based on prior entropy [11].

On the other hand, this method has some limitations like using this framework extraction of image features is not possible, in some color images neighboring colors might be similar, in those types of images the clustering could be complex which may result in poor segmentation of the image with this framework.

VI. APPLICATIONS

The automatic fuzzy clustering framework can be used in vast applications like biological applications for distinguishing the different species in an image. In medical applications for identifying different diseases in the human body, which can be identified using this framework and treated accordingly. Further, in navigation applications like maps for segmenting the traffic density and shows the traffic density in the route of the user, this helps the users to decide in which route they need to travel to reach their destination in shorter time [22], [23]. This framework can be used in clustering the weblog data to identify similar access patterns and can be also used in recognizing different communities in social networks. Fig. 5 shows the example of input and output of segmented image [1].



Courtesy: doi: 10.1109/TFUZZ.2019.2930030
Fig 5. Input and output of segmented images

VII. CONCLUSION

The method here proposed AFCF is the combination of the prior entropy, density peak clustering and the super pixel technology. It is able to overcome some of the drawbacks which are present in the existing algorithms like now as it can get the sum of clusters automatically in the proposed method and also better image segmentation results as it is being integrated with the super pixel and prior entropy, the proposed method can be applied for the real images as well as the synthetic images and comparatively AFCF could be the best among the other algorithms for image segmentation.

VIII. FUTURE SCOPE

In the proposed method, the use of color as the feature of the super pixel area which is actually a drawback like it cannot extract other features by using this algorithm. So, it can integrate the neural networks by that it can extract more features. Based on that feature, it can get more enhanced synthesized automatic image segmentation results.

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