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A Review of Challenges in Clustering Techniques for Image Segmentation

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Abstract: ***Image segmentation emerges as one of the important fields in image analysis. There are many image segmentation algorithms in literature and each has its own pros and cons. This paper deals with the cluster based image segmentation methods as it gives a new way of mathematical pattern to identify regions in an image. The paper presents an extensive review of clustering algorithms, which includes clustering algorithms and their improved versions. Various extended versions of K-means, FCM, Gravitational Clustering, optimized and hybrid clustering algorithms were studied and identify the major challenges and solutions in clustering techniques. This study helps researcher to find out the major issues in clustering algorithms for image segmentation.***

Keywords: Clustering Algorithms, Fuzzy c-means, Hierarchical Clustering, image segmentation, Iterative clustering, K-means algorithm.

I. INTRODUCTION

Image segmentation is a process of classifying an image into different regions where each region represents an object. It helps in the extraction of meaningful information from the image. The classification is achieved by labelling each pixel to a cluster or region according to some homogeneity criterion. There are various types of image segmentation techniques and the choice of a segmentation technique over another is decided by the type of image to be segmented and application for which segmentation is to be done. This paper focuses on cluster-based image segmentation techniques because of their robustness to noise. However, they may have high computational cost but with the advancement of technology, it is no longer an issue.

Thresholding method is considered as simplest image segmentation method. It is very good at segmenting grey images as an image is divided into object and background depending on the threshold value of pixels, where above threshold value pixel represents objects and below threshold value pixel is considered as background. But it is difficult to segment complex grey images as well as color images using thresholding method. Although multilevel thresholding methods are available to do segmentation of these types of images they fail to produce quality results [1]. To cope up with this situation clustering is proposed where the pixels of complex grey image or color image is deliberated to have multiple feature values and to classify these pixels, one has to consider some of these features. The features used for classification would be local properties over a neighbourhood of each pixel [2].

Clustering is defined as the grouping of a given set of objects into subsets according to the properties of each object. Each group is considered as the cluster where objects within clusters have similar attributes whereas objects outside the cluster have different properties. Each object has set of attributes that define it [3].

II. CLUSTERING ALGORITHMS

Clustering techniques are quasi-statistical techniques for forming classifications. The term clustering was first coined by Tryon in 1939 [4]. Clusters are defined as continuous regions of multidimensional space containing a set of pixels having similar features, separated by a distance from other such regions. In multidimensional feature space there are lots of features, so which features are considered for cluster classification is a big issue. This is solved by BC TRY system which provides users a solution. They replace all the features with a standard set of features without loss of generality that means a standard set will reproduce all the inter-correlations of all the features [5]. Classification of pixels into clusters should ensure that each pixel belongs to one and only one cluster and same pixels are assigned to same clusters whereas pixels of different clusters have to be different. This is called cluster problem. This problem is solved by defining the terms difference and similarity in a quantitative fashion that satisfies some optimality criterion called objective function [6].

Clustering techniques are mainly divided into two categories hierarchical and iterative [7]. These two categories represent different approaches to clustering which are difficult to compare. However, this paper reviews hierarchical and iterative approaches comparatively.

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A. Hierarchical Partitioning

Hierarchical methods of cluster analysis enforce hierarchical structure on the data. These structures are represented in the form of dendrograms. Hierarchical methods fall into two categories divisive and agglomerative.

In divisive clustering, the entire image is considered as a cluster and then splitting is performed recursively in a top-down manner. The division is performed on the basis of a single feature or multiple features [8] [9].

In agglomerative clustering, the bottom-up approach is used where observation starts in its own clusters and merges in a hierarchical manner. This method extends the cluster gradually by adding pixels or predefined clusters [10]. Agglomerative clustering is divided into a single [11] [12] and complete linkage clustering [9] which is based on linkage criterion. It specifies the dissimilarity of pixels as a function of the pairwise distances of observations in the pixels [13].

The dendrogram representation used in hierarchical clustering does not contain all information about the data and hence, efforts are required to make the dendrogram best fit for the data. So, that the effective clustering can be achieved.

B. Iterative Partitioning

Iterative partitioning is a novel method of data analysis and pattern classification using mathematical calculations. This technique works well when there is no prior information available about the data. (Iterative Self-Organizing Data Analysis Technique) ISODATA groups data into clusters determined by data itself [14] [15]. Iterative partitioning is mainly categorized into hard and soft clustering. The clustering techniques are divided into these two categories but to classify all clustering techniques into one of these categories is not simple. For the reason that the one algorithm includes many strategies to achieve segmentation and thus cannot be specifically categorized.

III.LITERATURE REVIEW

There are many clustering techniques proposed in the literature for grey as well as color images. Clustering techniques are a very good approach for classification of data in an unsupervised manner. This classification is obtained by solving the cluster problem by the objective function, which tells that if the appropriate partitioning is achieved or not. It only requires information about the measurement space that defines the measure of homogeneity and disparity that is a distance between two clusters [3]. This objective function is used in both hierarchical as well as iterative clustering methods.

The term cluster analysis was first coined and defined by TRYON in 1939 [4]. It represents the data as similarity matrix. In 1957 Michener and Sokal proposed a quantification method which uses correlation coefficients as a similarity measure and weighted variable group for classification [16]. Rogers and Tanimoto in 1960 developed a coefficient of association method for finding clusters [17]. In 1962 Rohlf and Sokal modified [16] by describing inter-relationship using correlation coefficient weighted pair method for factor analysis [18]. In 1967 Ball and Hall represented a clustering technique for multivariate data using Euclidean distance and average response pattern iteratively [15]. Although this method reduces the variety of responses within each group, however, it requires some improvements. Constantinescu in 1967 presented a multi-level clustering method using hierarchical clustering [19]. Haralick and Kelly in 1969 introduced two new iterative algorithms multiple-linkage chain clustering and eigenvector clustering based on measurement space and spatial constraints. Both the clustering algorithms require the prior knowledge of data as well as specification of K and e parameters, which are a number of clusters and probability cut off parameter respectively. Hence, the entropy method used to determine the values of K and e, which is not so efficient [20]. Then again in 1971 Haralick proposed another iterative algorithm which sub-optimally minimizes the probability of differences between the clusters [21]. This method fails to converge. An adaptive hierarchical clustering algorithm was proposed by Rohlf in 1970. This algorithm has the ability to adjust with the possible trends of deviation found within the clusters. It uses the inverse covariance matrices. [22]. This method is sensitive to the shape of clusters. In 1974 Buran and Odell presented a survey on cluster analysis. They present a review of various clustering algorithms based on measurement space and distance function [6]. These clustering algorithms are the monograph of the clustering algorithms and their aspects.

A. Image Segmentation by Clustering

An image consists of various features that can be considered for clustering. The grey image and color images consist of a large amount of information or data. This information is represented by various features which depend upon the type of image. Hence, the images are considered as multivariate data that needs measurement as well as spatial information for clustering.

A spatial approach to imagery clustering is proposed by Nagy in 1972 [23]. In 1973 Robertson and Jayroe and in 1975 Dinstein and Haralick also introduced spatial clustering algorithms for multi-image data [24] [25] [26] [27]. These algorithms able to cluster images into connected and homogeneous regions but much more refinement is required to get quality results. In 1979 Schachter et

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al. proposed an algorithm that does not consider spatial properties of the multi-spectral image but only based on the local features. It is difficult to select a single feature as a criteria for clustering as well as the results are not satisfactory [2]. An iterative procedure for clustering that depends upon the number of clusters was proposed by Ball and Hall in 1965 [14]. Coleman in 1979 extends this algorithm and introduced a faster algorithm for multi-spectral images [28]. Clustering algorithms for image segmentation mainly divided into two hard and soft categories, where hard clustering is called K-means clustering and soft clustering is called Fuzzy c-means clustering. K-means algorithm is considered as a good approach for image segmentation [29]. The K-means cannot converge optimally in general case. Fuzzy c-means (FCM) clustering is firstly proposed by Dunn in 1972 [30]. It uses unsupervised iterative optimization to approximate the minima of an objective function. It is the improved version of K-means. In 1973 Bezdek modified the Dunn's algorithm by using the membership function and Euclidean distance matrices to do clustering which leads to cluster validity problem [31]. Then in 1981 Bezdek introduced fuzzy c-lines to the fuzzy c-means[32]. Geman and Geman in 1984, presented a generalized K-means clustering algorithm [33]. In 1986, Cannon et al. presented an approximate Fuzzy c-means algorithm that replaces the exact value variables with approximate ones. It also uses efficient lookup table for Exponent and Euclidean distance which reduces the computation cost of FCM algorithm [34]. Although the convergence criteria is not clear. Then Trivedi and Bezdek proposed a low-level segmentation method, which uses the region growing method and pyramidal data structure along with FCM. This algorithm introduces blocky effect in results [35]. Lim and Lee in 1990, presented an FCM algorithm for color image segmentation. The main concern is to reduce the computational complexity of FCM but it fails, however gives quality results [36]. In 1992, Pappas proposed an adaptive K-means algorithm to include the spatial constraints and to account for the local intensity variations in the image. This method works well only for specific class of images [37]. Wu and Leahy in 1993, gave a novel graph approach where clusters are represented using undirected adjacency graphs. This method is not feasible for large images [38]. Krishnapuran and Keller introduced a possibilistic approach to clustering in 1993 which uses possibilistic approach instead of probability approach as used in FCM [39]. In 1994 Clark, presented a hybrid approach, combining knowledge-based techniques with fuzzy clustering. Fuzzy clustering provides an effective segmentation of brain images [40]. An efficient K-means clustering algorithm was proposed by Alsabti et al. in 1997 and Kanungo et al. in 2002. They use k-d tree structure and have low computational cost than K-means but not for all cases [41, 42]. The tree structure have to be recreated after a few iterations. Yung and Lai proposed a new gravitational clustering approach for color image segmentation [43]. Pham and Prince introduced an adaptive fuzzy c-means algorithm having a new objective function in 1998 [44]. It is robust to noise but having high computational cost.

TABLE I
Challenges of all the algorithms studied in the paper

Algorithm name	Techniques/criteria	Challenges/Issues
k-means	Similarity matrix [4], weighted matrix [16], correlation coefficient weighted pair method [18], within class variance [19], multiple linkage clustering and eigenvector clustering [20], Robert's gradient clustering [27], Gibb's Random Field[37] , tree structure [41], minimized square error [45] [46], hierarchical k-means [47],	Fails to converge optimally, requires prior knowledge of data, sensitivity to noise, application dependent, sensitive to the shape of clusters, dead centers, center redundancy
FCM	Minimum class variance [30], Euclidean distance [31], fuzzy c-lines [32], approximate values [34], thresholding FCM [36], Gaussian Kernel [44], k-d tree structure [48], spatial constraints [49] [50] [51], kernelized FCM [52], entropy based FCM [53], possibilistic clustering [39]	Less prone to local convergence, robust to noise as compared to K-means, cluster validity problem, increased computational cost, generates noisy image, initialization dependent, don't work well for multi-threshold segmentation, application dependent, center redundancy
Gravitational clustering	Markovian model [43]	Smooth and connected boundaries
Optimized K-means and FCM	Genetic algorithm [54-59], ant colony [60-62], Particle Swarm Optimization (PSO) [63], bird flocking [64], fireworks[65, 66], Genetic algorithm [67-69], PSO [70], ant colony [71]	Optimization techniques are used to optimize the performance, efficiency increases but the output has no significant improvement
Moving K-means and FCM	Moving centers based on objective function [72, 73]	Less Sensitive to noise and initialization, fast and accurate relatively
Hybrid K-means	SVM [74], PCA [75], Watershed [76-78], subtractive clustering [79]	The hybridization is done to improve the results

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In 1999 Krisna and Narasimha and Lu et al. in 2004 proposed a novel clustering algorithm which is a combination of k-means and genetic algorithm. Both algorithms considered K- means as crossover operator and distance matrix as mutation operator. However, the later one allows illegal strings which makes it faster than former[54] [55]. In 2007, Malyszko and Wierzchon presented a comparative analysis of standard and genetic K-means algorithm and found that the genetic K- means algorithm gives good values for individual validity indices but not for fitness function [56]. Tan and Lu in 2009 introduced a genetic K-means algorithm which utilized the feature and weight factors to improve the genetic K-means[59]. But it suffers from high computational efficiency. Min and Siquing in 2010 uses the genetic algorithm to find out the initial cluster centers for K-means. Although, the number of custer is still an issue [57]. In 2001 Ng et al. and 2010 Sarpe presented algorithms that are the combination of k-means and watershed algorithm [76] [77]. It is an improved K-medoid algorithm more efficient than [80].

A modified FCM called psFCM (partition Simplified FCM) was proposed by Hung and Yang in 2001 [48]. It speeds up the execution but the quality of results is same. In 2002 Pham introduced spatial constraint to the FCM which makes it more robust to noise but generates faint artifact at the edges [49]. In 2006 Chuang et al. introduced another FCM with spatial information. It reduces the spurious blobs and noisy spots [50]. Saha et al. in 2016 introduced circular shape function to FCM which helps in detection of pap smear cells [51]. New distance function called least square method is introduced to both k-means and fuzzy c-means algorithm by Wu and Yang in 2002 [81] and in 2004 kernel induced distance is introduced to FCM by Zhang and Chen [52] . In 2003 Szilagyi et al. introduced a new factor gamma to [82] to reduce the calculations[83]. In 2006 Fahim et al. and Zalik in 2008 proposed an efficient K-means algorithm that minimizes mean square distance to find the cluster numbers [45] [84].

In 2007 Zhao et al. proposed a k-means algorithm with Ant Colony Optimization algorithm. This improved algorithm reduces the computational complexity and accelerate the convergence but suitable only for grey images [56]. A fast and automatic genetic fuzzy algorithm is proposed by Nie et al. in 2007. This method resolves the difficulties of FCM that are initial cluster number and trapping in local minima effectively [56]. In 2007 two FCM algorithms are proposed for MR brain image segmentation. One algorithm uses Particle Swarm optimization and another uses genetic algorithm as optimization techniques to get effective results [70] [68]. Liu in 2009 segmented flame image using FCM and genetic algorithm [85]. In 2015, Jansi modified FCM using GA [69]. But all these methods introduced only for MR brain segmentation and may be modified so that can be applied on other type of images. In 2008 Cheng et al. proposed a FCM with the combination of Genetic algorithm as well as Ant Colony Optimization [71]. It enhances the accuracy of segmentation and gives better results when compared to [70] [68].

An entropy constrained FCM algorithm proposed by Junwei in 2007 that only focused on reduction of execution time [53]. In 2009 Isa et al. proposed an adaptive Fuzzy moving K-means algorithm. It overcomes the redundancy problem as well as effect of trapped center at local minima but requires more time for processing [72]. In 2011, Siddiqui and Isa presented an enhanced Moving k-means algorithm which is an improved version of [86]. It simply outperforms the conventional clustering algorithms and less sensitive to cluster variance [73]. In 2012, Chebbout et al. presented a comparative study of k-means, Partitioning Around Mediods method (PAM) [80] and Kohonen's Self Organizing Map (SOM) [87] [88]. The results shows that the K-means and SOM gives better segmentation results than PAM [89]. In 2013, Jabar et al. presented an adaptive k-means algorithm for blood cell segmentation. This algorithm includes k-means algorithm combined with mean shift algorithm. This only works for blood cell images [90]. In 2013, Sinha and Deb proposed an intelligent clustering technique that uses Bird Flocking optimization [64]. In 2015, Dhanachandra et al. proposed an algorithm that uses subtractive clustering algorithm for the selection of cluster centers and then k-means is applied. The proposed algorithm overcomes the initialization problem of k-means algorithm [79]. Liu and Guo proposed an MRI image segmentation strategy that uses K-means and support vector machine [74] and Katkar et al. presented an algorithm which consists of Principle Component Analysis method and k-means clustering [75]. In 2016, Al-Dmour and Al-Ani proposed an MR brain image segmentation algorithm. It utilizes unsupervised and semi-supervised algorithms [91]. Bala and Sharma in 2016, proposed an algorithm that involves k-means algorithm and morphological edge detection algorithm. It segments the color images efficiently [92]. In 2017 Misra and Si proposed a fireworks algorithm for image segmentation [65].

IV. CONCLUSIONS

Clustering algorithms for image segmentation are considered as one of the most efficient and effective algorithms. They can effectively segment the colored and complex images along with the grey images. Clustering algorithms are of various types such as Hierarchical clustering, gravitational clustering, Possibilistic clustering, probability clustering, K-means, Fuzzy c-means, Mountain clustering, Intelligent clustering and subtractive clustering. All these clustering techniques are studied in this paper and found that each algorithm has its own pros and cons. K-means and Fuzzy c-means clustering are mostly used clustering algorithms.

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These clustering algorithms have three major problems first the results are totally dependent upon the initialization step that includes cluster number and cluster initialization, overlapped clusters and trapping of clusters in local minima. These are the issues that highly affect the segmentation results and lead to human intervention. The K-means algorithms also affected by noise present in the image, which is overcome by Fuzzy c-means but not so efficiently, hence it also requires research to make a noise robust clustering algorithm. Fuzzy c-means algorithm may also lead to under or over-segmentation. To overcome these limitations many improvements are carried out on these algorithms, which gives better results but not so efficiently that one is considered as best clustering algorithm. As one algorithm tried to overcome one issue may fail in another. All the modulations are according to the type of image to be segmented or type of processing model to be used. So, there is no specific clustering algorithm that works well for all kind of images and is platform independent. Further research can be to develop a clustering algorithm that is fully automatic, robust to noise, does not require prior knowledge, efficient and can segment all types of images with equal efficiency.

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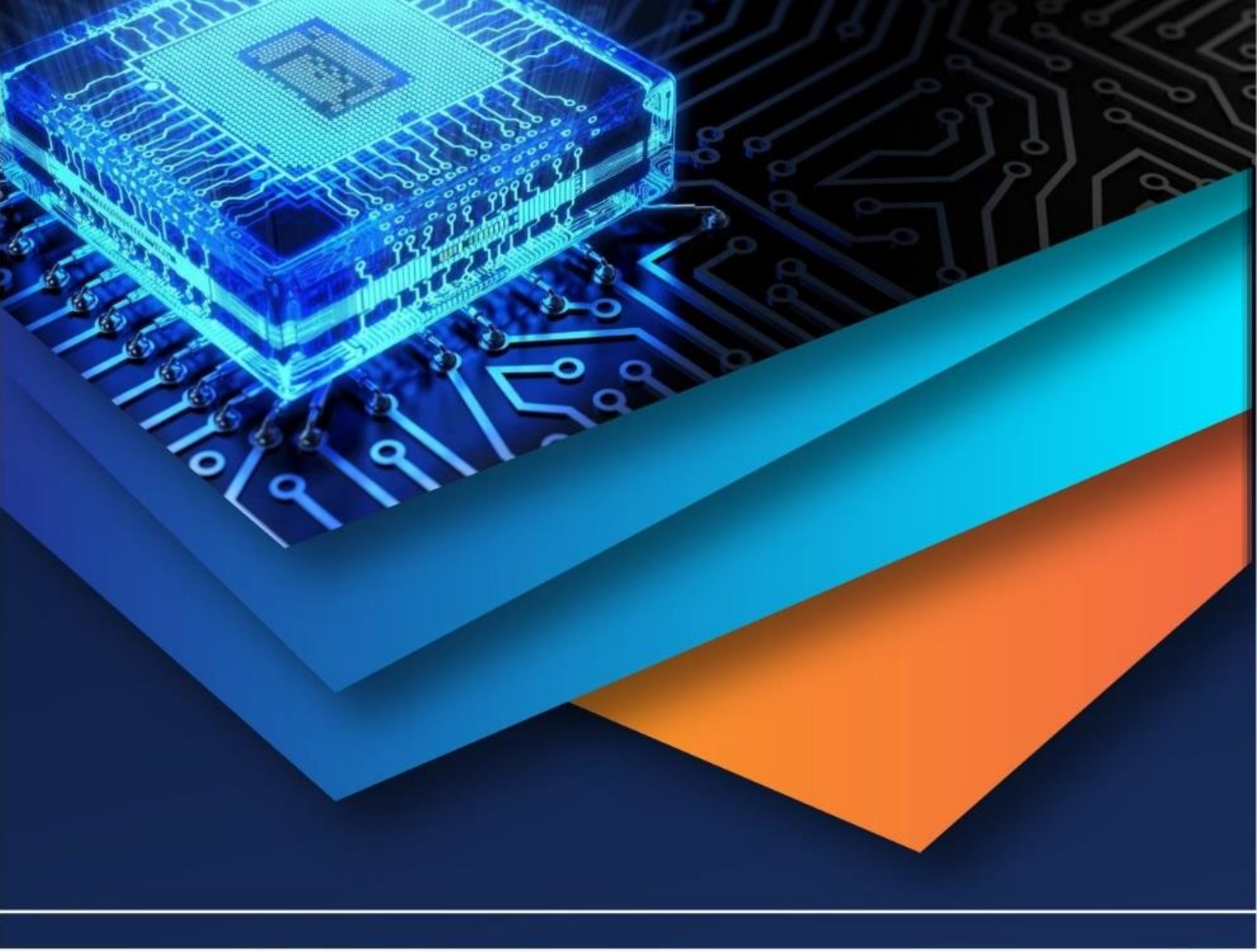

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