Color Image Clustering Based On Over Segmentation Using Superpixel

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Abstract- *There is a great number increase in the usage of image segmentation in this modern Computer vision and AI world, which is used in many applications like self-driving cars, early detection of cancers, robotics, video surveillance, etc; As the complexity of the application increases the higher precision of segmentation is required with less execution time. To increase the precision rate need to involve the spatial information. As involve the spatial information, the execution time has been increased. So in this method, calculating a variable and an adaptive windowing technique is used to involve the spatial neighbouring pixels which vary with image structure. In this work there are two types of noise are applied, one is additive white Gaussian noise (AWGN) and another one is salt & pepper noise at different noise levels. This work presents the image segmentation using FCM technique and Over segmentation method. The segmented image is next subjected to qualitative and quantitative analysis using two metrics which are Accuracy and RMSE. This algorithm not only produces high precision but also good noise removing capability compared to all the FCM versions.*

Keywords- FCM, over segmentation, Accuracy, RMSE.

I. INTRODUCTION

In the modern Computer Vision and AI world, Color Image Segmentation plays a major role which is the key step for next image processing steps such as Image recognition, object tracking, object classification, etc; In the field of image segmentation there have been lot many algorithms were implemented but still there have been lot many challenges are facing due to noise, background, non-uniformity, low signal to noise ratio, intensities, etc; For a single image there are multiple best segmentation solutions, it is difficult to find the fast and effective segmented one.

There are lot of definitions for image segmentation, a Simple and meaningful one is “Segmentation is a process of breaking down the image into meaningful regions or parts which is easily understandable by machines”. A popular definition for segmentation is” Segmentation is the process of partitioning a image into small segments or small regions or small parts based on color, structure, pattern, texture, gradient of brightness”. Image Segmentation is used to locate the specific location of the object and boundaries of object. More precisely it is method of assigning labels to every pixel in the image so that same label pixel contains certain related characteristics. Image segmentation techniques deals with gray scale images, binary images, color images.

Color image Segmentation is the process of separating the foreground of the image from the background of the image, this separation is done based on the similarity of color. This color image segmentation varies with the choice of color space. In general, RGB color space is the general color space with far different from the human eye perception. There are many color spaces which is used in image processing, some of them are Lab Color space, HSI color space, Ycbcr color space, etc. These color spaces are formed by CMY and CMYK Color models. Lab color space is most used and better representation of color images, which is the approximated human vision and less computational for image processing.

In the era of pictures and videos capturing through cameras and other devices has been rapidly increasing. So people need to see and understand the world around us, image segmentation has become a necessary technique for teaching machines how to understand the world around them. This image segmentation gently assists in powering handling technologies like automated medical imaging or automated medical diagnostics, self driving cars, robotics, etc. In medical applications it can be easily predict the future effecting diseases like cancer by understanding the CT scan, MRI scan, etc. In autonomous vehicles, reacting to the environment by noticing the actions of pedestrians, sidewalks, traffic signals, vehicles, etc. In Robotics the pixel level understanding that image segmentation provides can help robots to navigate their work spaces.

II. RELATED WORK

In this chapter discussion is about some of recent and important papers on the FCM and modified FCM’s. As there are many modified FCMs, to discuss about them is difficult, so picking some of the useful papers among them and discuss it. Before starting the discussing about all the modified Fuzzy

C Means Clustering algorithms, firstly need to understand clearly what Fuzzy C Means Clustering (FCM) is and then later discuss briefly about advantages, disadvantages and limitations for each and every modified Fuzzy C Means Clustering.

Fuzzy C-Means clustering is a soft clustering method in which each data item is given a probability or likelihood score to belong to the cluster. With a probability, a data point may belong to multiple clusters. For overlapped data sets, fuzzy c-means clustering produces better performance. It is a data clustering process in which a data point is divided into N clusters, with each data point in the dataset belonging to one of the clusters to some extent. A data point in the middle of a cluster, for example, has a higher degree of membership in that cluster, while a data point far away from the center of a cluster has a low degree of membership.

All the modified FCMs can be grouped into two categories. First one is based on employment of neighborhood information with fixed window size and shape. Example of this category is FCMS [1], FCMS-1[2], FCMS-2[2], FG-FCM [3], FLICM [4], ND-FCM [5], KW-FLICM [6], etc; Second Category has adaptive type employment of neighborhood information into the objective function instead of fixed window. Examples of this type are Liu's algorithm [10], Bai's algorithm [12], adaptive FLIC-M, other HMRF based Clustering [13-15], etc; both the categories have simultaneous advantages and disadvantages one on other.

FCM-S adds the spatial information in the objective function of FCM. But context information is insensitive to noise up to some extent. FCM-S is only suitable for Euclidean structure but not suitable for non-L2 normal structures of input. FCM-S includes lot of computational complexity and increase the execution time due to addition of spatial information to objective function. To overcome all these kernels based FCM-S1, FCM-S2 is introduced. Kernel calculates the mean and median filtering of spatial information before the spatial information added to objective function such that the execution time can be reduced to some part. FCM-S1 and FCM-S2 mainly includes three things. They are 1.it is can also capable of calculating for non-Euclidean distance measure, 2.increasing the robustness of noise and outliers, 3.retaining the mathematical complexity as simple as possible. There are many kernel-based versions some of them are support vector machine kernel, kernel F-LDA, kernel PCA, kernel perception algorithm. Kernel helps to converts lower dimensional to higher dimensional feature by non linear mapping. Higher dimension is achieved by mapping the inner product in the original space. The advantages of kernel are interpreting cluster results, easy copying of dataset with missing values, calculating non Euclidean measure, making the computational simplicity. Mean and Median filtering corresponds to FCMS-1 and FCMS-2 respectively. KFCM-S2 [3] is trade-off between execution speed and robustness to noise.

III. PROPOSED WORK

The main goal of proposed algorithm is to acquire high color-segmentation accuracy with very low root mean square error (RMSE) value. This can be achieved by choosing an adaptive neighboring window that varies with an input image to include the local spatial information.

The block diagram of proposed method is shown in figure below.

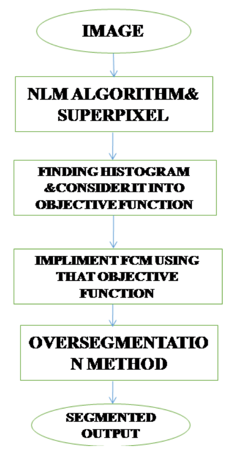


Figure1: block diagram of proposed method

In this method, there are four steps to achieve color segmentation. They are

1. Firstly Superpixel image is implemented by Multiscale Morphological Gradient Reconstruction Watershed (MMGR-WT) to obtain accurate contour of the object.
2. Calculate Color Histogram for the above super pixel and involve the histogram into the objective function
3. Implement the FCM based on the above objective function.
4. Finally, applying over segmentation method for FCM segmented output to achieve high accuracy.

3.1 Super pixel by MMGR-WT

The Steps followed for calculating the superpixel by MMGR-WT are as follows

i.Filtering ii.Gadient Image
iii. Implement MMGR iv. Apply Watershed

i. Filtering

Non-local means is an algorithm in image processing for image denoising. Unlike "local mean" filters, which take the mean value of a group of pixels surrounding a target pixel to smooth the image, non-local means filtering takes a mean of all pixels in the image, weighted by how similar these pixels are to the target pixel. This result in much greater post-filtering clarity and less loss of detail in the image compared with local mean algorithms. If compared with other well-known denoising techniques, non-local means adds "method noise" (i.e. error in the denoising process) which looks more like white noise, which is desirable because it is typically less disturbing in the denoised product.

ii. Gradient image

The object's edge is represented by discontinuous local image characteristics, with the most relevant portion of the image changing in local brightness. A spatial domain differential operator is often used to detect edges. Prewitt, Roberts, and Sobel are the most often used first-order differential operators. Non-linear operators such as the Laplacian, Kirsch, and Wallis operators are being used in the second-order differential operator… One kernel is actually 90 degrees rotated from the other. The Roberts Cross operator is very close to this. It is calculated for both x component and y component direction and adds up by using the modulus operator where one detects horizontal components and other detects the vertical components. Edge preserves the more information of the object so the focus is mainly on the edge details for any application. As the edge detection becomes the preprocessing technique in the image processing.

iii. Morphological Operations

If Watershed is applied directly without applying Multiscale Morphological gradient reconstruction then it is over segmented easily and becomes noise sensitive. After applying the sobel operator, the Morphological operations are to be performed. The basic Morphological operations are Dilate and Erode. Morphological techniques use a small shape or prototype called a structuring element to probe an image. The structuring factor is placed in all possible positions in the image and compared to the pixels in its immediate vicinity. Any operations determine whether the element "fits" into the neighborhood, while others determine whether it "hits" or intersects it.

Erosion

Erosion is a removing the pixels around the object with a certain radius. The neighbor pixels of the object of a foreground are removed with a structuring parameter .Erosion removes the smaller objects in the background. It removes the unnecessary pixel noises from the image. Erosion is a compressing operation which compresses the pixel around the neighbor pixels. It separates the closed placed objects by removing the common pixels.

Dilate

Dilation is an expanding operation which expands the around the pixels with based the structuring element. Dilation helps to fill the holes in the image. It is used to remove the unnecessary noise in the foreground. It connects the regions which were separated by small gap.

Multiscale Morphological Gradient Reconstruction (MMGR)

In MGR the problem is choosing the different r value for different images. So the aim is to remove the dependency of SE on the segmented regions. For that make a different reconstruct images with Multiple SE values. By calculating the point wise maximum of the Multiple SE images can achieve an excellent gradient image which removes the local minima and preserves only the important image details. If applied Watershed directly without applying Multiscale Morphological gradient reconstruction then it is over segmented easily and becomes noise sensitive. Even though calculate Multiple SE and Take point maximum need to give the range of Choosing SE i.e., r1, r2. If r1 (lower limit) is chosen as very high value then very low contour precision will attain. If lower value of r1 is chosen then very high contour precision will attain. Generally the r1 is value chosen as 2. The upper limit r2 value controls the size of the superpixel region. It's better to have a higher r2 value. As r2 value increases there is no significant change in the superpixel image. So r2 value is removed after with some convergence.

iv. Watershed

Watershed segmentation is a method that uses image morphology to segment regions. It necessitates the selection of at least one internal marker (seed point) for each picture item, including the backdrop as a distinct object. Any grayscale image may be regarded as a topographic surface, with peaks and hills denoting high intensity and valleys denoting low intensity. You begin by filling isolated valleys (local minima) with a variety of colored water (labels). River from separate valleys, plainly of various hues, will start to blend as the water rises, depending on the neighboring peaks (gradients).To avoid this; you construct barriers where water meets water. You keep filling the water and erecting obstacles until all of the peaks are submerged. The segmentation outcome is then determined by the obstacles you created. The image is split into two separate sets: watershed basins and watershed lines, if flood this surface from its minima and prevent the waters from separate sources from combining. The catchment basins should conceptually correspond to the uniform grey level sections in this image if apply this adjustment to the picture gradient. The below figure2 shows the watershed process.

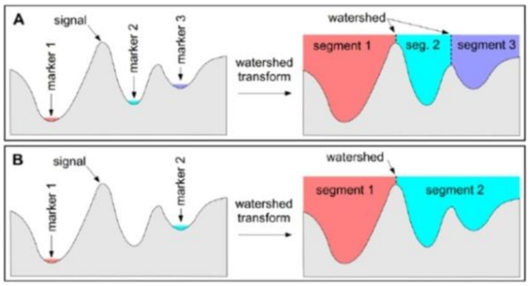


Figure2: Diagram of watershed process

3.2 Histogram based Objective function

The histogram of the superpixel image is to be calculated. As there are very less number of intensity levels in histogram due to the superpixel, The mean of all the superpixel region is to be found and note down how many number of pixels are present in that superpixel region. These histogram values are introduced in the objective function, so that the objective function can choose adaptive and variable neighboring local spatial information, which discarded the distance calculation between current pixel and clustering centroid. Due to mean region of superpixel adding only one pixel value among them and give the count of number of pixels in that region. So that the computational complexity is reduced. The EnFCm Objective function is given by

$$J_m = \sum_{k=1}^{q}\sum_{i=1}^{c} \gamma_k (u_{ki})^m \|\xi_k - v_i\|^2$$

Where m- represents the fuzziness index

u_{ki}- represents the membership function of k^{th} data point to i^{th} clustering center

γ_k- the number of pixels in gray level,

v_i–represents the cluster centers

q– the total number of gray level intensities

c– represents the total number of clusters

3.3 FCM

By using EnFCM objective function, it extends to color images using the superpixel intensity values. The objective function for proposed method is given by

$$J_m = \sum_{l=1}^{q}\sum_{k=1}^{c} s_k u_{kl}^m \left\| \left(\frac{1}{s_l}\sum_{p\in R_l} x_p\right) - v_k \right\|^2$$

Where m- represents the fuzziness index

u_{kl}- represents the membership function of k^{th}data point to l^{th} clustering center

s_l- the number of pixels in l^{th} intensity level,

v_k–represents the cluster centers

q– the total number of gray level intensities

c– the total number of clusters

x_p– the color pixels in p^{th} intensity level

3.4 OVER SEGMENTATION METHOD

For some images it is not possible to set segmentation process parameters, such as a threshold value, so that all the objects of interest are extracted from the background or each other without over segmenting the data. Over segmentation is the process by which the objects being segmented from the background are themselves segmented or fractured into subcomponents.

The goal of over segmentation method is to get a rather small set of segments that don't cross object boundaries. This method performs well when the segment boundaries overlap with the other, and then it partially covering only a single objects region. It significantly reduces the amount of data in an image without loss of information

IV. RESULTS AND DISCUSSION

The proposed method gives good ACCURACY and RMSE values when compared with existing method. So, the results obtained have visually good ACCURACY and RMSE values. The proposed method resulting images are shown in figures 3, 4, 5, 6, 7, 8, 9 and 10.

Fig.3 and fig.4 shows the clustering images with different noise levels of additive white Gaussian noise.

Fig.5 and fig.6 shows the clustering images with different noise levels of Salt & Pepper noise

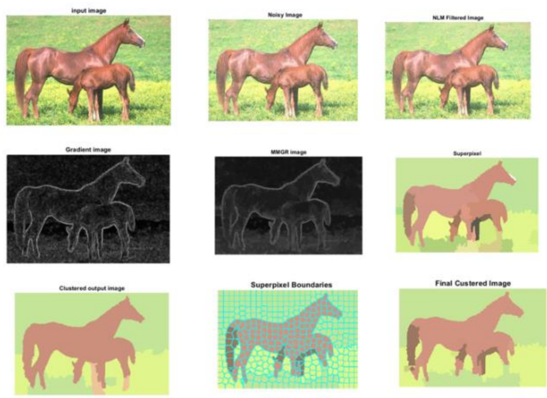


Figure3: Output images with AWG noise level of 10%

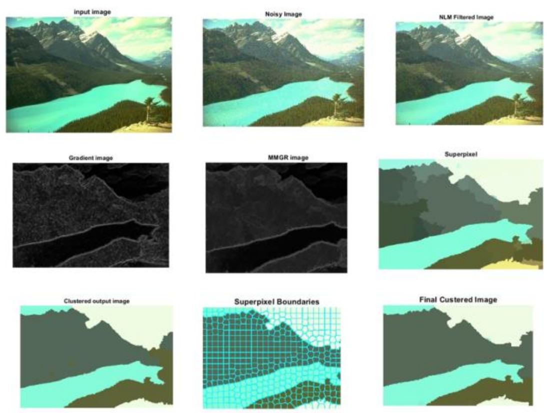


Figure4: Output images with AWG noise level of 20%

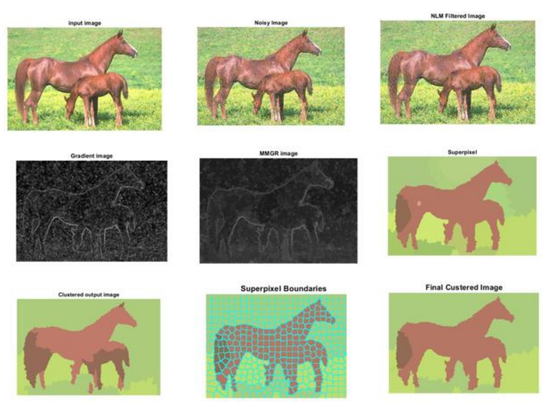


Figure5: Output images with Salt & Pepper noise level of 10%

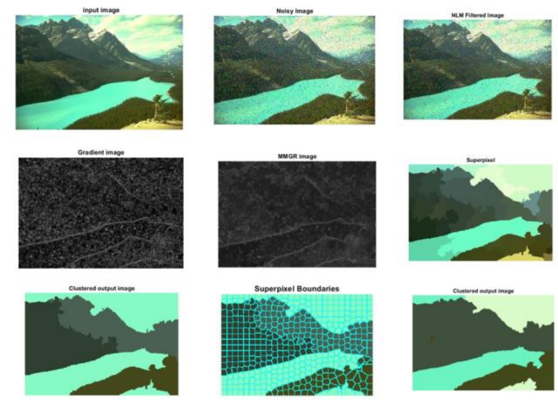


Figure6: Output images with Salt & Pepper noise level of 20%

From fig7 to fig10 shows the clustering output images with different cluster sizes. These are the outputs for proposed method without adding any noise.

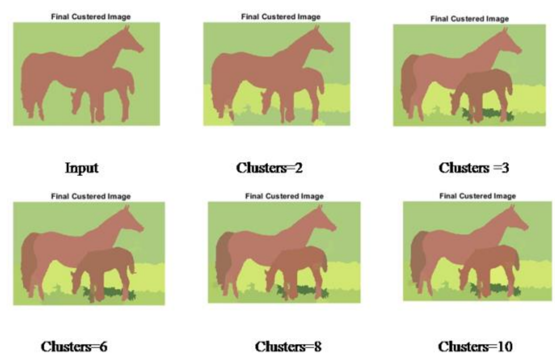


Figure7: Output images after clustering for different cluster size

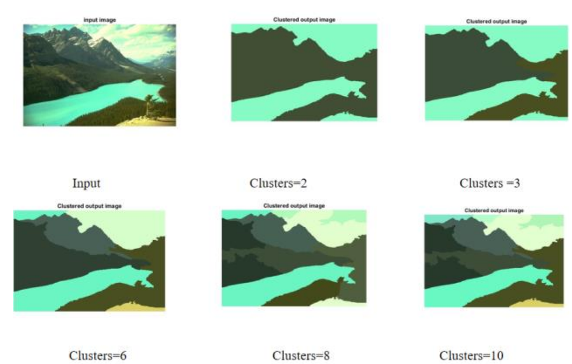


Figure8: Output images after clustering for different cluster size

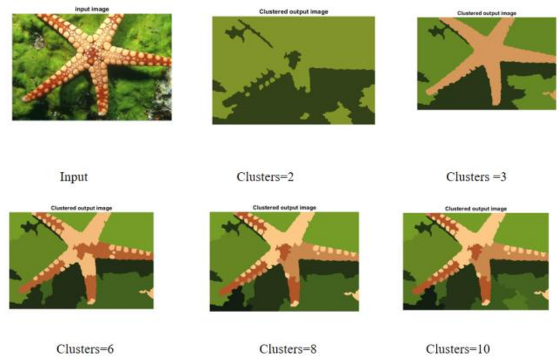


Figure9: Output images after clustering for different cluster size

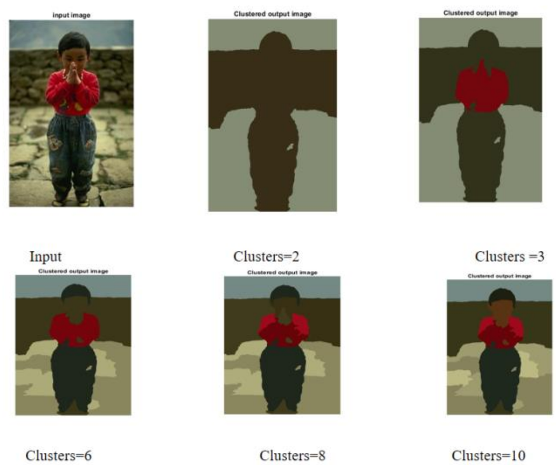


Figure10: Output images after clustering for different cluster size

QUALITATIVE ANALYSIS:

Accuracy and RMSE is calculations for the proposed method with existing methods and the results are shown in table1 and table 2.

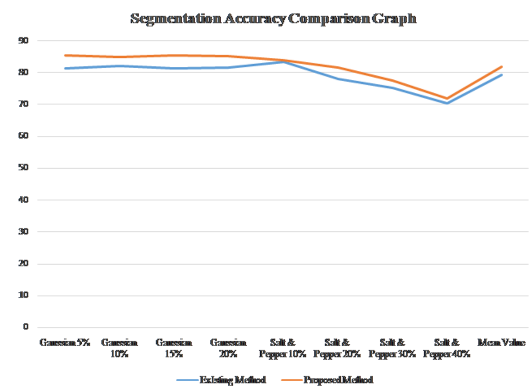
Table1: Comparison of Accuracy between existing and proposed method

Segmentation Accuracy Comparison Table		
Noise	**Existing Method**	**Proposed Method**
Gaussian 5%	81.24	**85.33**
Gaussian 10%	82.24	**84.85**
Gaussian 15%	81.29	**85.39**
Gaussian 20%	81.63	**85.03**
Salt & Pepper 10%	83.41	**83.9**
Salt & Pepper 20%	78.11	**81.63**
Salt & Pepper 30%	75.33	**77.53**
Salt & Pepper 40%	70.33	**72.03**
Mean value	79.1975	**81.96125**

Table2: Comparison of RMSE (root mean square error) between existing and proposed method

Root Mean Square Error Comparison Table		
Noise	**Existing Method**	**Proposed Method**
Gaussian 5%	9.96	**9.35**
Gaussian 10%	9.95	**9.04**
Gaussian 15%	9.47	**8.53**
Gaussian 20%	8.77	**7.8**
Salt & Pepper 10%	9.32	**9.08**
Salt & Pepper 20%	9.54	**9.15**
Salt & Pepper 30%	9.84	**9.23**
Salt & Pepper 40%	10.11	**9.53**
Mean value	9.62	**8.96375**

The accuracy levels and RMSE levels of the proposed model is indicated in Figure 11. The results show that the proposed model accuracy rate is high. The RMSE represents the loss in output image, so it should lesser in proposed method in figure below.



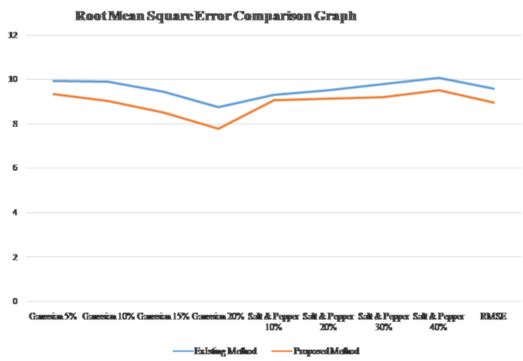


Figure11**:** Accuracy levels and RMSE levels of the proposed model

From the above tables and figures in the proposed method, it is evident that for the images at different noise levels the Accuracy is achieved as 81.9625 with AWGN and salt and pepper noise. Using this approach, for images the Accuracy value achieved is greater than the existing methods.

The RMSE of proposed method is achieved as 8.96375; it is less than the existing method is shown in above table 2 with different AWGN and salt and pepper noise.

V. CONCLUSION & FUTURE SCOPE

This algorithm on unsupervised clustering for the color image segmentation using histogram based Fuzzy C means clustering and over segmentation method. This method gives segmented output for high accurate segmentation which can be used in complex applications like medical field, satellite imaging, Autonomous Car, robotics, etc; In this work, all the results were implemented from the BSDS Dataset. There are mainly two benefits achieved from the project 1. Involving the spatial information into the objective function by using the superpixel that helps to choose the variable irregular window shape which requires less computation 2.Good Superpixel technique which detects the good boundary with good image details preservation. In the objective function the data points on the basis of distinct color intensity levels instead of pixels has been calculated, which are very less due to the superpixel. This proposed method results compared with existing method using only FCM which provides better accuracy and RMSE with good Color segmentation.

In this method the clustering type color segmentation has been implemented which has very little execution time and good contour segmentation with high accuracy. The disadvantage of this algorithm is we have to choose the number of clusters manually. In the future scope, there can be an algorithm that automatically chooses the number of clusters required for the clustering with faster execution time and more accurate segmentation.

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