



# International Journal of Marketing Management

ISSN 2454 - 5007



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Email ID: [editor@ijmm.net](mailto:editor@ijmm.net) , [ijmm.editor9@gmail.com](mailto:ijmm.editor9@gmail.com)

## Comparative Analysis of Proposed Methods for Analysing Color Pixel based Image Segmentation Using Tiger Image Dataset.

Ramaraj.M\*1, Dr.S.Niraimathi\*2

**Abstract:** Image segmentation is a plays the vital role of image partitioning into multiple region (pixel clustering). The aim of segmentation is to obtain a new image in which it is easy to detect regions of interest, localize objects, or determine characteristic features such as edges. Image segmentation is one of the important methods to classify the pixels of an image correctly in a decision oriented application. It divides an image into a number of discrete regions such that the pixels have high similarity in each region and high contrast between regions. Segmentation is the partition of a digital image into regions to simplify the image representation into something that is more meaningful and easier to analyze. Considering that an image can be regarded as a tiger image dataset in which each pixel has a spatial location and a color value, color image segmentation can be obtained by clustering these pixels into different groups of coherent spatial connectivity and color. Conservation of tiger has been the challenging task. This work would add a small account to the herculean task of conserving the species. This work proposes an algorithm from which the age of the tiger can be inferred. This work combines the domain of image processing with data mining to infer the age of tiger. This research work proposes a method to find the age of the tiger, using color as a parameter. Color pixel based image classification and clustering techniques has been used to identify the age of the tiger.

**Key words:** image segmentation, clustering, age calculation, FBISODATA, FBMC, Enhanced K-Means clustering algorithm, time complexity and accuracy.

### INTRODUCTION

Clustering is a strategy that arranges the simple information judiciously and looks through the concealed examples that may exist in datasets. It is a technique for gathering information objects into muddled groups with the goal that the information in a similar cluster are comparable, yet information having a place with divergent group vary [12]. They require for sorting out the sharp rising information and taking in selective data from information, which makes clustering strategies are broadly connected in numerous application regions, for example, man-made consciousness, science, client

relationship administration, information pressure, information mining, data recovery, picture preparing, machine picking up, promoting, solution, design acknowledgment, brain science, measurements et cetera. [4] K-means a numerical, unconfirmed, non-deterministic, iterative technique. It is straightforward and quick, so in numerous down to earth applications, the strategy is turned out to be an extremely compelling way that can deliver huge clustering comes about concern. In any case, it is extremely reasonable for creating globular clusters [7]. The k-means

1 Research Scholar, 2Associate Professor, Department of Computer Science,NGM College, Pollachi, India.

[ramaraj.phdcs@gmail.com](mailto:ramaraj.phdcs@gmail.com), [niraisenthil@hotmail.com](mailto:niraisenthil@hotmail.com)

calculation is compelling in creating clusters for some reasonable applications in developing regions like Bioinformatics. Be that as it may, the computational difficulty of the interesting k-means calculation is high. Besides, this calculation brings about various kinds of clusters relying upon the irregular

#### **RELATED WORK**

K. A. Abdul Nazeer et al [1] describes the major problem of the k-means algorithm is about selecting of initial centroids that completely produces different clusters. But final cluster quality in algorithm depends on the selection of initial centroids. Two phases includes in unique k means algorithm: first for

centroids and a resourceful way for assigning data points to clusters. But still there is a limitation in this enhanced algorithm that is the value of k, the number of preferred clusters, is still mandatory to be given as an input, regardless of the allotment of the data points. Shi Na et al. [2] has proposed the analysis of shortcomings of the standard k-means algorithm. As k-means algorithm has to analyze the distance between each data object and all cluster centers in each iteration. This repetitive process affects the efficiency of clustering algorithm. Chen Qi et al. [21] describes a new clustering algorithm of text mining based on improved density clustering. The clustering algorithm based on density is widely used on text mining model for example the DBSCAN(density based spatial clustering of application with noise) algorithm DBSCAN algorithm is sensitive in choose of parameters, it is hard to find suitable parameters. In this paper a method based on k-means algorithm is introduced to estimate the E neighborhood and min pts. Finally an example is given to show the effectiveness of this algorithm. Kamran Khan et al. [22] presents the summary information of the different enhancement of density-based clustering algorithm called the DBSCAN. The purpose of these variations is to enhance DBSCAN to get the well- organized clustering results from the fundamental datasets. In addition it also Highlights the research contributions and found out some limitations in different

decision of starting centroids. This composition manages a heuristic method in light of association and dividing the data information for choice enhanced beginning centroids, accordingly enhancing the exactness of the k-means calculation.

determining initial centroids and second for assigning data points to the nearest clusters and then recalculating the clustering mean. But this enhanced clustering method uses both the phases of the original k-means algorithm. This algorithm combines a systematic technique for ruling initial

research depicts the critical evaluation in which comparison and contrast have been taken out to show the similarities and differences among different authors' works. The spatiality of this work is that it uncovers the writing survey of disparate DBSCAN solution and gives a tremendous measure of data under a solitary paper. Md. Sohrab Mahmud et al. [23] has proposed an algorithm to compute better initial centroids based on heuristic method. The newly presented algorithm results in highly accurate clusters with decrease in computational time. In this algorithm author initially compute the usual score of each data points that consists of multiple attributes and weight factor. Merge sort is applied to sort the output that was previously generated. The data points are then divided into k cluster i.e. number of desired cluster. Finally the nearest possible data point of the mean is taken as initial centroid. Experimental results show that the algorithm reduces the number of iterations to assign data into a cluster. But the algorithm still deals with the problem of transfer quantity of desired cluster as input.

#### **METHODOLOGY**

##### **FUZZY MOUNTAIN CLUSTERING ALGORITHM**

The mountain clustering method is a grid-based procedure for determining the approximate locations of cluster centers in

data sets with clustering tendencies [23]. The efficient approach to approximate estimation of cluster centers on the source of a density measure called the mountain function. The rules that are associated with higher values of the peaks of the mountain function determined. From the centers of the clusters that are obtained by the mountain function process are determinant the initial estimates of the parameters of the reference antecedent and resultant fuzzy sets of the principles [20].

$$M(v) = \sum N$$

$$\exp \left( - \frac{\|v - x_i\|^2}{2\sigma^2} \right)$$

Where  $x_i$  the  $i$ th data point and  $\sigma$  is application specific constant implies that each data point  $x_i$  contributes to the height of the mountain function at  $v$ , and the contribution is inversely proportional to the distance between  $x_i$  and  $v$ . The mountain function can be viewed as a measure of data density. The constant  $s$  determines the height as well as the smoothness of the resultant mountain function [18]. This procedure of updating the mountain capacity and decision the

following bunch focuses proceeds until the point when an adequate number of group focuses are accomplished.

Pseudo Code:

```
Initialization;
Forming grid  $V$  in the data space;
Construction of mountain function;
    Computing mountain function values of the patterns in database;
    Set  $i=1$ ;  $k=0$ ;
    While  $i \leq \text{length}(\text{database})-1$ 
         $k=k+1$ ;
        Creating a new cluster  $C_k$ 
        The pattern  $x_i$  is replicated to  $C_k$ 
         $j=i+1$ ;
```

```
        While  $j \leq \text{length}(\text{database})$ 
            if cluster valley  $(x_i, x_j) = 0$ 
                The pattern  $x_i$  is replicated to  $C_k$ 
                Deleting  $x_j$  from database;
                 $j=j-1$ ;
            end if
             $j=j+1$ ;
        end while
         $i=i+1$ ;
    End while
```

Figure 1: Fuzzy Based Mountain Clustering Algorithm

### FUZZY ISODATA ALGORITHM

ISODATA is curtailed as Iterative Self-Organizing Data Analysis Technique. ISODATA is a technique for unsupervised arrangement.

Try not to need to know the quantity of bunches. Calculation parts and unions bunch. Client characterizes limit esteems for

- Initialize  $t=0$ ,  $\theta_j(t)$  for  $j=1 \dots m$ .
- Repeat until  $\|\theta(t) - \theta(t-1)\| = 0$
- -For  $i=1$  to  $N$ 
  - Find closest rep. for  $x_i$ , say  $\theta_j$ , and set  $b(i)=j$
- -For  $j=1$  to  $m$ 
  - Set  $\theta_j = \text{mean of } \{x_j \in X: b(i) = j\}$

parameters. The calculation goes through much cycle until the point that esteem is come to. ISODATA Algorithm [21], which enables the measure of bunches to be

balanced naturally amid the emphasis. By consolidating comparative and part bunches with vast standard deviations.

Haphazardly put the group focus sand the pixels are relegated in light of the base separation to the inside technique [20]. The standard deviation inside every last one of the group, and the separation between bunch focuses is ascertained.

Pseudo Code:

- Guaranteed to converge to global minimum of  $j$  if squared Euclidean distance used.
- If e.g. Euclidean distance used, cannot guarantee this form.
- Initialize again
- Repeat until termination condition met
- -For  $i=1$  to  $N$  (assign mem. Values to  $f.v.$ 's)

For  $j=1$  to  $m$

$$u_{ij}(t) = \frac{1}{\sum_{k=1}^m \frac{1}{\left(\frac{d(x_i, \theta_j)}{d(x_i, \theta_k)}\right)^{\frac{1}{q-1}}}}$$

$t = t + 1$

$\mathcal{P}$

$$\sum_{i=1}^N u_{ij}^q (t-1) \frac{\partial d(x_i, \theta_j)}{\partial \theta_j} = [0]$$

For  $\theta_j$  and set  $\theta_j(t)$  equal to it

- Example termination condition: stop when  $\|\theta(t) - \theta(t-1)\| < \epsilon$ , where  $\|\cdot\|$  is any vector norm and  $\epsilon$  is user specified.

Figure 2: Fuzzy Based Iterative Self-Organizing Data Analysis Techniques

1. Clusters are part on the off chance that at least one standard deviation is more noteworthy than the client characterized edge.
2. Clusters are joined if the separation between them is less than the client characterized limit.
3. A second cycle is performed with the new group focuses.

4. Encourage emphasess are performed until:

The standard between focus remove falls lesser than client characterized limit

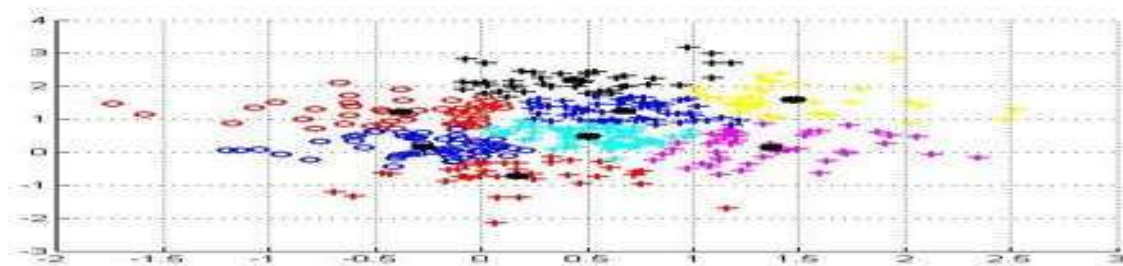
The standard change in the between focus remove between emphasess is not as much as a limit.

The most extreme number of cycles is come to.

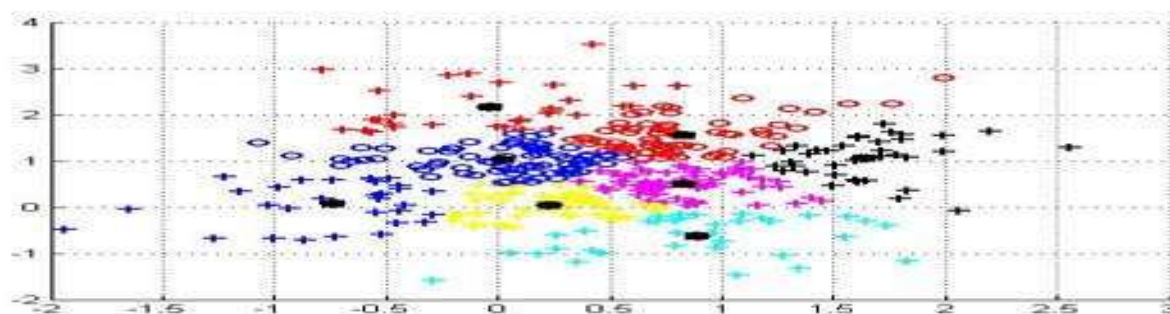
## RESULTS AND DISCUSSION

This paper focuses on the systems that have collected 500 different images of an adult tiger. They differentiate the image with different colors. Clustering is done on the different age group of tigers and with the different skin color and stirpes. It is segmented based on different ages and colors of the tiger. By clustering each images are grouped by its difference in the age and color. By segmenting each different image, the same

color image segmentation approach, the real time tiger image data sets has been used. The data sets are collected from various resources on the web page and the data set has varying types of size and colors of images and they too differ in the format as .gif, .jpg, .png, .trf. Image segmentation process is implemented and demonstrated using MATLAB. The version of MATLAB is 8.6(2015b) and corei3 processor, graphics card on nvidia and support for other system facilities as to use.



FBM clustering



ISODATA clustering method

age and the same color images are clustered.

In order to check the performance of our

Figure 3: Data clustering for both the proposed algorithms

Table 1: Data clustering for 10, 50 and 100 iteration to be performed by the Existing and Proposed methods

The above table 1 shows that the data clustering for existing and proposed methods like M-K-Means, FBISODATA, FBMC is 10, 50 and

	10 iterations		50 iteration		100 iteration	
	accuracy	time period	accuracy	time period	accuracy	time period
M-k-Means	86.9	3.52	90.56	2.25	92.3	2.43
FBMClustering	95.4	1.32	94.2	1.1	96.4	0.32
FBISODATA	93.4	0.43	94.8	0.66	96.3	0.74

100 iteration for the real time tiger image

dataset. These algorithms are

compared taking is to account both accuracy and time period calculation for the real time tiger image dataset. Where the FBMC algorithm accuracy level is higher than the other algorithms and



loss execution time is taken on these algorithm. When these algorithms are compared with the other algorithms and much efficient result to be generate the FBMC

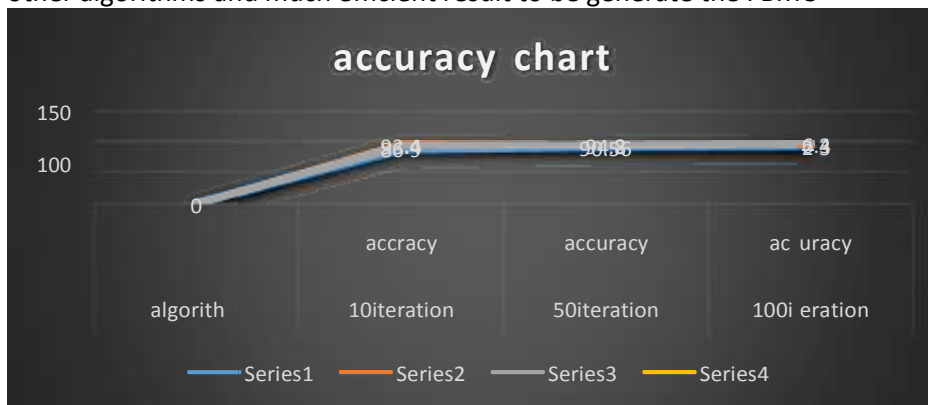


Figure 4: Overall accuracy chart on da a (tiger image dataset) clustering for existing and proposed methods as 10, 50 and 100 iteration.

The above figure 4 shows that the data clustering for 10, 50 and 100 iteration compared with the accuracy of Existing and Proposed methods as K-Means, M-K-Means, FBISODATA and FBMC clustering. The accuracy chart is figure on table 1.

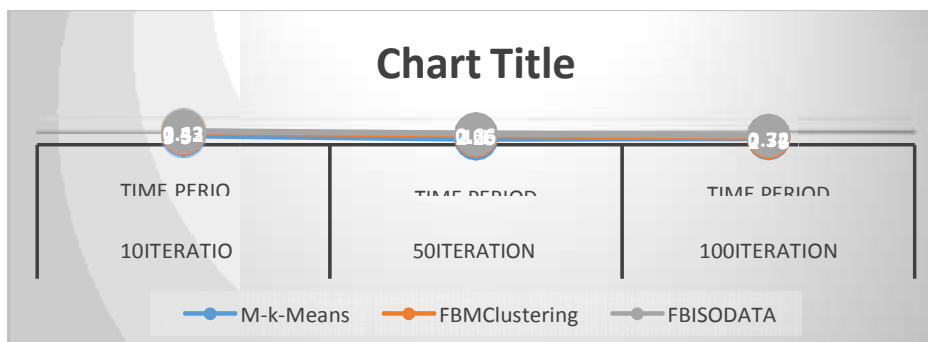


Figure 5: overall time period calculation for the real time dataset (tiger image), data clustering with the existing and proposed methods on 10, 50 and 100 iterations.

The above figure 5 shows that the data clustering for 10, 50 and 100 iteration compared with the time period calculation of Existing and Proposed methods as K-Means, M-K-Means, FBDBSCAN, FBISODATA and FBMC clustering. The overall time period calculation is based on table 1.

## CONCLUSION

This paper proposes a new clustering algorithm namely as M-K-Means, FBISODATA

(Fuzzy Based Iterative Self organizing Data Analysis Techniques Algorithms) and FBMC (fuzzy Based Mountain Clustering) and these are all the techniques has been done this paper. The proposed algorithms can execute the high performance result will be generated.

The clustering result much effective and efficient process to be handle with the tiger image dataset,when compared the results of the proposed methods has more efficient. The highest accuracy rate on FBMC in 100 iteration is 96.4% and lowest accuracy rate on the proposed algorithms as K-Means, M-K-Means, FBDBSCAN, FBISODATA is 92.4%,

94.2%, 96.3%, 92.3% respectively and difference between these algorithms as 4% is K-Means, 4.1% is M- K-Means and 0.1% is FBISODATA, these all algorithms comparing with FBMC and execution time is taken by the individually as 1.12sec is K-Means, 2.43sec is taken by M-K-Means, 0.32sec is taken by FBMC and 0.74sec is taken by FBISODATA respectively and minimum execution time is taken by FBMC for 0.32sec. So, the highest accuracy rate on FBMC is (96.4) and loss execution time (0.32) during the running time and generated the better clustering results on FBMC(Fuzzy Based Mountain Clustering Algorithm). Future research work is to improvement of accuracy and reduction is time complexity. The results are evident highly with increase is iterations. These factors shows that that the evident results with increasing iteration.

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