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Design and Implementations of Color Pixel Based Image Segmentation using Enhanced Data Clustering Algorithms to Applying on Tiger Image Dataset

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Key words: Image segmentation, clustering algorithms, k-means, modified k-means, FBISODATA, FBDBSCAN and FBMC

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Abstract: Tiger has become the reserve animal. Conservation of tiger has been the challenging task. This research would add a small account to the herculean task of conserving the species. This research proposes an algorithm from which the age of the tiger can be inferred. This research combines the domain of image processing with data mining to infer the age of tiger. Image processing techniques like image enhancement and segmentation plays a vital role in mining the image of the tiger. The image processing is complemented with data mining to find the age of tiger where data mining plays the role of analyzing the statistical report of confirming the age of the tiger. Several scientific researchers have carried out their research on the tiger reserve conservation. 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. Clustering is a part which considers the principal of systematic techniques in handling. Clustering is the process of making a group of abstract objects into classes of similar objects. Image segmentation is the classification of an image into different groups. Many researches have been done in the area of image segmentation using clustering. There are different methods and one of the most popular methods is k-means clustering algorithm. In working on k-mean clustering approach to cluster the data. Several strategies have been proposed for enhancing the performance of k-means clustering algorithm. DBSCAN is designed to discover clusters of arbitrary shape. DBSCAN which exploits its characteristics and at the same time improves its limitation, so, it is used widely in the clustering technique. The Mountain Clustering (FMC) method is a relatively simple and effective approach to approximate estimation of cluster centers on the basis of a density measure. ISODATA algorithm (Iterative Self-Organizing Data Analysis Technique Algorithm) which allows the number of clusters to be adjusted automatically during the iteration by merging similar clusters and splitting clusters with large standard deviations. The Modified k-Means Clustering (MKMC) and Fuzzy ISODATA (FISODATA), FBDBSCAN, FBMC cluster for making the algorithms much less time consuming, greater high-quality and efficient for higher clustering accuracy rate with reduction is time complexity.

INTRODUCTION

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. It is a valuable tool in various fields including health care, image processing, traffic image and pattern recognition, etc. There are different methods for image segmentation like threshold based, edge based, cluster based and neural network based of which one of the most efficient method is the clustering method. Then again there are different types of clustering like k-means clustering, fuzzy C-means clustering, mountain clustering and subtractive clustering methods. One of the often used clustering algorithm is the k-means clustering. It is quite simple and computationally faster when compared to the hierarchical clustering. It can also research with the large number of variables. But it produces different cluster result for different number of number of cluster. So, it is required to initialize with the proper number of number of clusters, say k = 2. Again, it is required to initialize the k-number of centroids.

Different value of initial centroids would result in different clusters. So, selection of proper initial centroid is also an important task. Image segmentation has become one of important tool in medical research where it is used to extract the region of interest from the background. So, medical images are segmented using different technique and processed outputs are used to carry out further analysis. But medical images in their raw form are represented by the arrays of numbers in the computer with the number indicating the values of relevant physical quantities that show contrast between different types of body parts. The FCM calculation is touchy to introductions; bunching calculations regularly require the client to determine the quantity of group focuses and their areas. The nature of the arrangement depends emphatically on the decision of the underlying qualities. Fluffy ISODATA (FISODATA) which is an expansion of FCM calculation refreshes group number amid the calculation; it has an ability of self-arranging by part and combining bunches. The reason for this paper is to think about FCM and FISODATA comes about. k-means clustering, fuzzy DBSCAN clustering and fuzzy mountain clustering. k-means clustering is one of the simplest methods of learning algorithms and then it solves the well-known clustering problems. Density Based Spatial Clustering of Application with Noise (DBSCAN) is a data clustering algorithm. It is the widely used algorithm. DBSCAN can find arbitrarily shaped clusters. It can even find a cluster completely surrounded by a different cluster. DBSCAN requires only two parameters and is for the most part indifferent to the requesting of the focuses in the database. The fuzzy mountain clustering process is the process of determining the approximate locations of cluster centers in data sets with clustering tendencies[1].

Literature review: Bhogal *et al*.[2], describes image segmentation as the basis of image processing, comprehension and model identification and a hot research subject of image processing technologies. Color image segmentation using the neural networks, k-means clustering algorithm has yielded fruitful results. An advantage resulting from the choice of color space representation could be taken to enhance the performance of segmentation processes.

Mandvikar[3], describes contour analysis as a method to describe, store, compare and find the object presented in the form of exterior outlines, solve the main problems of a pattern recognition-transposition, turn and a rescaling of the image of object. CA methods are invariant to these transformations. It provides more realistic interaction. It is an advance method and could be a promising technology for motivating users to engage in learning systems.

Jumb *et al*.[4], the HSV color space is similar to the way human eyes perceive color, hence, in this method, first RGB image is converted to HSV (Hue, Saturation, Value) color model and V (Value) channel is extracted as value corresponds directly to the concept of intensity/brightness in the color basics section. The HSV color space is similar to the way human eyes perceive color, hence in this method, first RGB image is converted to HSV (Hue, Saturation, Value) color model and V (Value) channel is extracted as value corresponds directly to the concept of intensity/brightness in the color basics section.

Ballerini *et al*.[5] the k-Nearest Neighbor (k-NN) algorithm depends critically on its being given a good metric over the input space. The k-Nearest Neighbor (k-NN) algorithm uses only the geometric distance to measure the similarity and the dissimilarity between the objects without using any statistical regularities in the data which could help convey the inter-class distance. Gulati and Panwar[6], image segmentation is a set of segments that collectively cover the entire image or a set of contours extracted from the image. The quality of segmentation depends upon the quality of image.

The segmentation is based upon the measurement taken from the image and might be grey level, texture, color, depth or motion[7]. Models are computer generated curves that move within the image to find object boundaries under the influence of forces of curve and image itself. One may visualize the active contour as a band or rubber band of arbitrary shape that is deforming with time trying to get as close as possible to the object contour.

Nazeer and Sebastian[8] 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 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 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.

Na *et al*.[9] 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 *et al*.[10] 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 study 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 etc. 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 research depicts the critical evaluation in which comparison and contrast have been taken out to show the similarities and differences among different author's works. The spatiality of this research is that it uncovers the writing survey of disparate DBSCAN solution and gives a tremendous measure of data under a solitary study.

Mahmud *et al*.[11] 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.

Raju *et al*.[12] presents a comparative analysis between k-means clustering algorithm and fuzzy clustering algorithm. In this study the researcher also discuss the advantages and limitations of fuzzy ISO algorithm. K-means is a partional based clustering algorithm whereas fuzzy ISO is non partional based clustering algorithm.

MATERIAL AND METHODS

Image segmentation: Segmentation is a process by which an image is partitioned into multiple regions (pixel clusters). 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[13]. As a result, the image obtained by the segmentation process is a collection of disjoint regions covering the entire image whereby all the pixels of a particular region share some characteristic or property such as color, intensity or texture.

Color Based Image Segmentation (CBIS): Segmentation is subdividing an image into its constituent regions or object. The level up to which the subdivision is carried out depends on the problem being solved[7]. While different ethnic groups have different levels of the melanin and pigmentation, the range of colors on is clearly a subspace of the total color space, assuming that a person framed is not having face with any unnatural color.

Color segmentation and pattern matching: In general, color-based image segmentation, object identification and tracking have many applications in machine vision. Many targets can be easily segmented from their backgrounds using color and subsequently can be tracked from frame to frame in a video stream. Furthermore, the targets can be recognized and tagged using their color signature[14].

Pattern matching: The pattern matching is consists of a set of pattern elements and it is continuously duplicated for a complete print pattern. If the distributions of pattern elements with identical color, shape and orientation can be identified, the repeat patterns in a complete printed pattern can be obtained.

Pre-processing process: The pre-processing stage is based on removed from unwanted noise of image or pixels. Which techniques to apply on the pre-processing or post processing to be use on Wiener filter techniques. The Wiener filter is the MSE-optimal stationary linear filter for images degraded by additive noise and blurring. Wiener filters are often applied in the frequency domain[15]. The Wiener filtering executes an optimal trade off between inverse filtering and noise smoothing. It removes the additive noise and inverts the blurring simultaneously.

Contrast enhancement method: Contrast enhancement is a process that makes the image features stand out more clearly by making optimal use of the color available on the display or output device. Contrast manipulations involve changing the range of values in an image in order to increase contrast. The following method as Contrast Limited Adaptive Histogram Equalization Method (CLAHE) is used for improve the visibility level of foggy image or video[16] is to be used CLAHE enhancement method for improving the video quality in real time system. Adaptive Histogram Equalization (AHE) is different from normal histogram equalization because AHE use several methods each corresponding to different parts of image and used them to redistribute the lightness value of the image and in case of CLAHE "Distribution" parameter are used to define the shape of histogram which produce the better quality result compare then Adaptive Histogram Equalization (AHE).

Contour analysis: Contour analysis is used for pattern recognition task on the image. Let us take the image a size n*n pixels. Then breed its uniform grid step by step[17]. The total length of all grid lines is: L = 2n2/s as the image in the form of contours already has natural segmentation is divided into contours it is possible to carry out a filtration of parts of the image to simple indications.

Proposed clustering techniques

Fuzzy DBSCAN algorithm: DBSCAN stands for Density-Based Spatial Clustering of Applications with Noise. Density-Based Spatial Clustering of Applications with Noise (DBSCAN) is most widely used density based algorithm[18]. It is widely used in network security and data mining. Density reachability and density connectivity are used concept in DBSCAN. Density reachability-a point "p" is said to be density reachable from a point "q" if point "p" is within e distance from point "q" and "q" has adequate number of points in its neighbors which are within distance ε. Density connectivity-a point "p" and "q" are said to be density connected if there exist a point "r" which has adequate number of points in its neighbors and both the points "p" and "q" are within the ε distance. The advantage is it does not require an apriori requirement of number of clusters and it is able to identify noise data while clustering[19] Algorithm:

Algorithm 1: Fuzzy based density based spatial clustering and application with noise algorithm

```
Input: a data set D
Output: arbitary shape clusters
For eah data point p in D do
  If p is not mark as 'seen' then
    Mark p as 'seen'
     Find N, (p, D)/* find ∈ neighborhood of data point p/*
If (N, (p, D))/< Min Pts then
  Mark data point cluster id as noise
Else
Cluster id = cluster id+1
End if

For all q ∈ N, (p, D) do
Mark data points qas 'seen'
 Find N, (q, D)
 If |N, (q, D)|> minpts then
        Give data point' q a cluster id
      End if
    End for
   End if
 End for
```

Pseudo code; Algorithm:

Let X = {x_1, x_2, x_3, ..., x_n} be the set of data points. DBSCAN requires two parameters: ε (eps) and the minimum number of points required to form a cluster (minPts)

1) Start with an arbitrary starting point that has not been visited
2) Extract the neighborhood of this point using ε (All points which are within the e distance are neighborhood)
3) In the event that there is adequate neighborhood around this point at that point grouping process begins and point is set apart as went by else this point is marked as commotion (Later this point can turn into the piece of the bunch)
4) If a point is found to be a part of the cluster then its ε neighborhood is also the part of the cluster and the above procedure from step 2 is repeated for all ε neighborhood points. This is repeated until all points in the cluster are determined
5) A new unvisited point is retrieved and processed, leading to the discovery of a further cluster or noise[9]
6) This process continues until all points are marked as visited

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[10]. 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[14].

$$M(v) = \sum_{i=1}^{N} \exp\left(-\frac{\|v - x_i\|^2}{2\sigma^2}\right)$$

Where:

x_i : The ith data point
s : An 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[20]. 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; Fuzzy based mountain clustering algorithm:

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_length (database)-1
    k = k+1;
    Creating a new cluster Ck
    The patten xi is replicated to Ck
    j = i+1
    While j_length (database)
  If cluster valley (xi, xj) = 0
    The pattern xi is replicated to Ck/
    Deleting xj from database
    j = j-1
end if
j = j+1
end while
i = i+1
End while
```

Modified k-means algorithm: This algorithm partitions the entire space into unique segments and calculates the frequency of data point in every segment. The segment which has maximum frequency of data point can have the maximum probability to contain the centroid of cluster[18, 15]. Similar like the traditional k-mean algorithm the number of cluster's centriod (k) will be provided by the user and the number of divisions will be k*k ("k" vertically as well as "k" horizontally). A simple data structure is required to store some information in every iteration which is to be used in next iteration. This technique avoids calculating the distance of each data object to the cluster centers repeatedly and thus, the running time is saved. This technique can effectively recover the speed of clustering and accuracy, reducing the computational complexity of the k-means[2].

M-K-means Algorithm; an modified k-means clustering algorithm:

Compute the distance of each data-point di (1< = I< = N) to all the centroids Cj (1< = j< = k) as d (di, Cj)
2. For each data-point di, find the closest centroid Cj and assign di to cluster j
3. Set cluster Id[i] = j; // j:Id of the closest cluster
4. Set Nearest_Dist[i] = d(di, Cj)
5. For each cluster j(1< = j< = k), recalculate the centroids;
6. Repeat
7. For each data-point di, a. Compute its distance from the centrroid of the present nearest cluster; b. If this distance is less than or equal to the present nearest distance the data point stays in the cluster; c. Else for every centroid cj (1< = j< = k) compute the distance d (di, Cj); d. End for
8. Assign the data-point di to thecluster with the nearest centroid Cj
9. Set cluster Id[i] = j
10. Set Nearest Dist[i] = d(di, Cj)
11. End for (step (2))
12. For each cluster j(1< = j< = k), recalculate the centroids until the converence criteria is met.

Algorithmic steps:

Let D = {d1, d2, ...dn} be the set of n data items and k be the number of desired clusters
For each column of the data set, determine the range as the difference between the maximum and the minimum element
1. Identify the column having the maximum range
2. Sort the entire data set in non-decreasing order based on the column having the maximum range
3. Partition the sorted data set into "k" equal parts
4. Determine the arithmetic mean of each part obtained in step 4 as c1, c2….ck, ...,
5. Take these mean values as the initial cancroids
6. Repeat
7. Allocate each data item di to the cluster which has the nearby centroids
8. Calculate new mean of each cluster; until convergence criterion is met

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 parameters. The calculation goes through much cycle until the point that esteem is come to. ISODATA algorithm 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[14]. The standard deviation inside every last one of the group and the separation between bunch focuses is ascertained:

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

Pseudo code; fuzzy based iterative self-organizing data analysis techniques:

- Initialize t = 0, $\theta_j(t)$ for j = 1...m
- Repeat until $\|\theta(t)-\theta(t-1)\| = 0$
- -For i = 1 to N
    - Find closest rep. For x_i, say θ_j and set b(I) = j
- -For j = 1 to m
    - Set θ_j = mean of $\{x_j \varepsilon X: b(I) = j.\}$
- Guaranteed to converge to global minimum of j if squared Euclidean distance used
- If e.g., Euclidean distance used, cannot guaranteed this form
- Initialize again
- Repeat untill termination condition met
- -For i = 1 to N (assign mem. Values to f.v.'s)
  For j = 1 to m

$$u_{ij(t)} = \frac{1}{\sum_{k=1}^{n}\left(\frac{d(x_i,\theta_f)}{d(x_j,\theta_f)}\right)x^{\frac{1}{(q-1)}}}$$

-t = t+1

R

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

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

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

RESULTS AND DISCUSSION

This study focuses on the system that have collected 500 different images of an adult tiger. They differentiate the image with different colors (Fig. 1). 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 age and the same color images are clustered. In order to check the performance of our 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.

Figure 1 represents the data clustering for proposed methods like M-k-means, FBDBSCAN algorithm, FBISODATA clustering algorithm and FBM clustering algorithm and these all the proposed algorithm to process with original tiger image dataset on. Every clustering method is to process with highly efficient cluster the data and it makes the better performance of clustering and well known understanding of the cluster the result of the proposed methods.

Figure 2 is represented by the segmentation of color object to the color image segmentation. Color pixel is

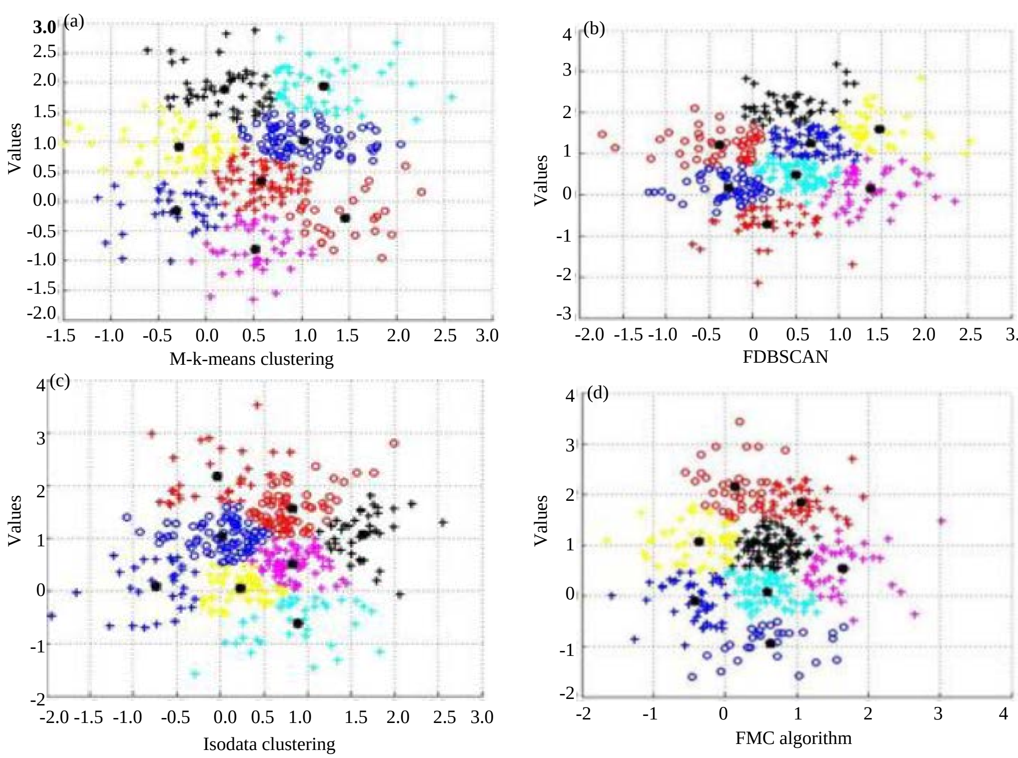

Fig. 1(a-d): Data clustering for the proposed algorithm

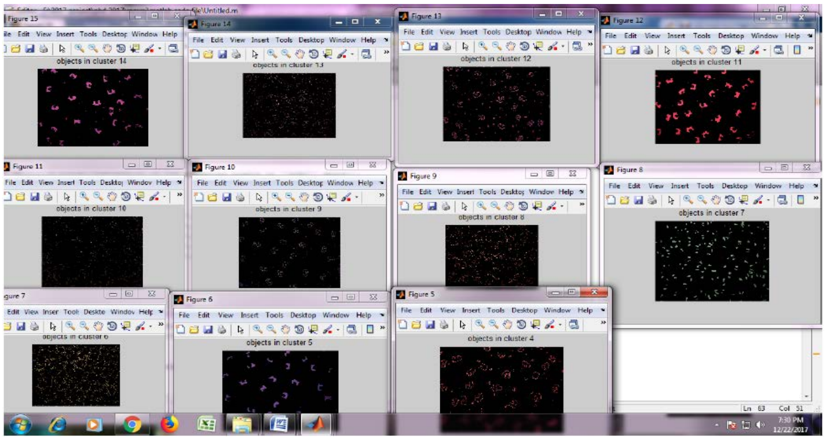

Fig. 2: Color pixel classification

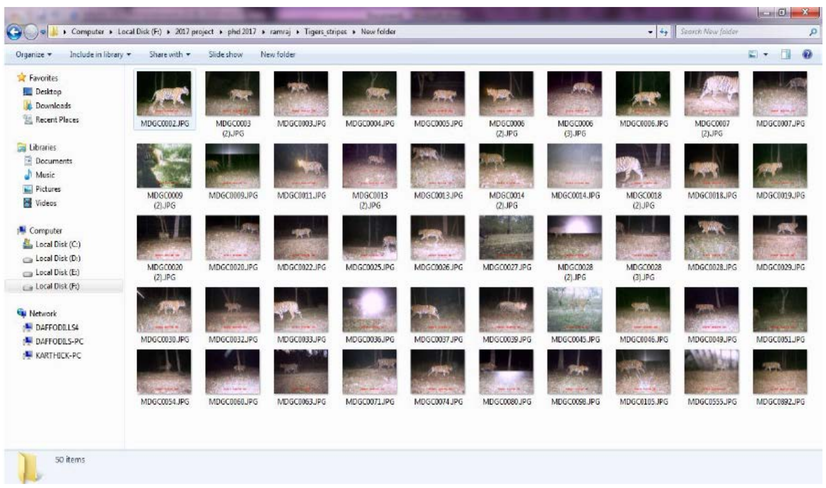

Fig. 3: Real time tiger image dataset

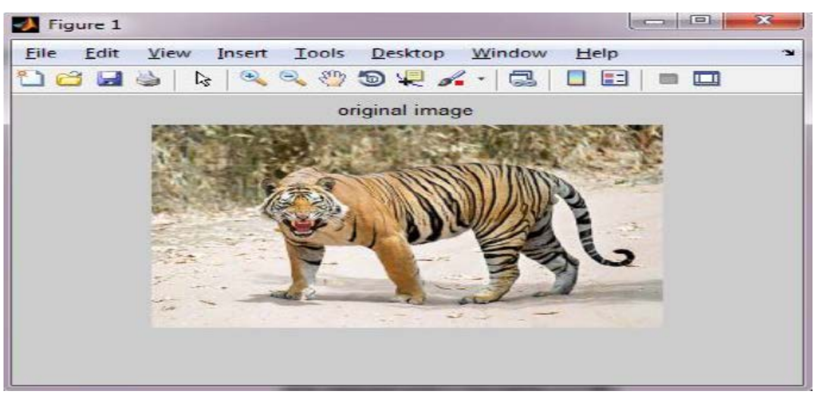

Fig. 4: Original input image

separated into the color image, color images has adapted into multiple color pixel in the single image and it is separate the individual color pixels to the separate window.

Figure 3 and 4 shows that the real time tiger image dataset. To collect the various resources on the tiger image and it store the image database. To be collect the nearly 500 and above, original tiger images to be collected

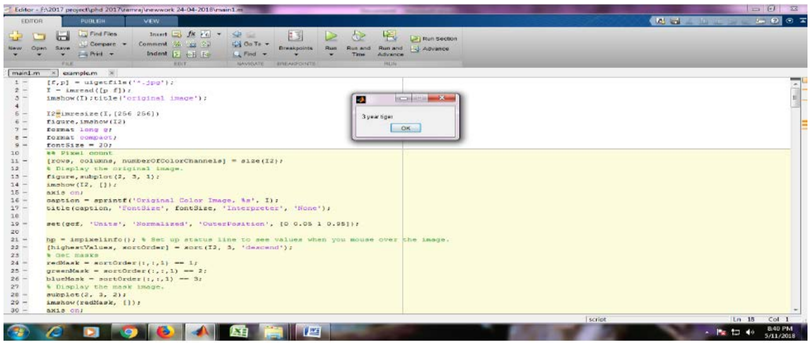

Fig. 5: Find the age of tiger and it is based on original image

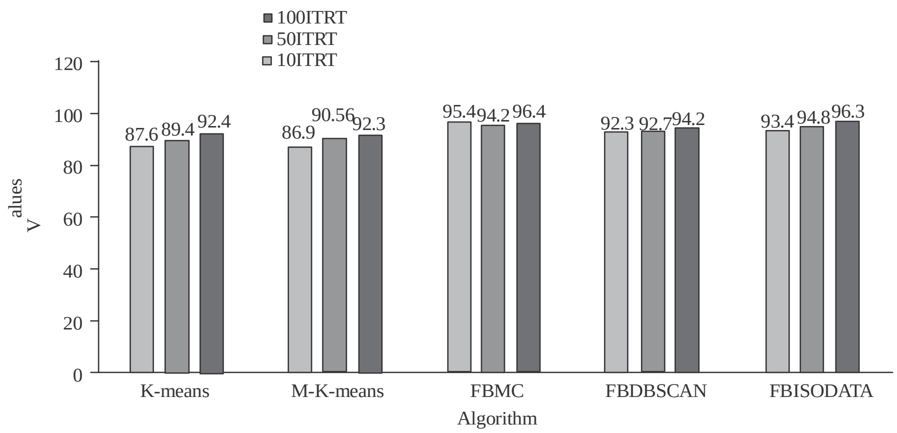

Fig. 6: Overall accuracy chart on data (tiger image dataset) clustering for existing and proposed methods as 10, 50 and 100 iterations: accuracy chart

the different adult tiger and different age group of tiger images are used our research work and it has been done in the field of research.

Figure 5 is represents to find the tiger age is based on the input original image as Fig. 4. Find the age calculation of the tiger using parameter are used only skin color. The skin color is based on RGB value and calculate the pixel value of color and set the range between the each color is based on RGB (Fig. 6).

Accuracy calculation: The accuracy of a test is its ability to differentiate the tiger age cases correctly. It can find the correct classified the tiger age is based on the skin color to estimate the pixel values. To estimate the accuracy of a test, we should calculate the proportion of true positive and true negative in all evaluated condition. Mathematically, this is basically used formula for all:

$$\text{Ac} = \frac{\text{TP+TN}}{\text{TP+TN+FB+FN}}$$

Yet another formula as is given to calculate the accuracy calculation for the image dataset as:

$$\text{Ac} = \frac{\text{Correct classified image (age)-Unclassified image (age)}}{\text{Total No.of image (age)}} \times 100$$

where Ac is calculate the correct classified image (age) and unclassified image (age) is divided by total No. image (age). The age is calculated by the color pixel values and it helps to identify the correct age of the tiger (it's not an accurate age and is given assumption for the tiger age). Set the key value is based on the color pixel value of RGB. The range of RGB color pixel values is to find the known and unknown age of tiger using tiger image dataset.

Table 1 shows that the data clustering for existing and proposed methods like k-means, M-k-means, FBDBSCAN, FBISODATA, FBMC is 10, 50 and 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 then 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.

Table 1: Data clustering for existing and proposed methods on 10, 50 and100 iteration to the real time tiger image dataset

	10 Iterations		50 Iterations		100 Iterations	
Variables	Accuracy	Time period	Accuracy	Time period	Accuracy	Time period
k-means	87.6	0.56	89.4	0.89	92.4	1.12
M-k-means	86.9	3.52	90.56	2.25	92.3	2.43
FBMC	95.4	1.32	94.2	1.1	96.4	0.32
FBDBSCAN	92.3	2.56	92.7	1.5	94.2	1.62
FBISODATA	93.4	0.43	94.8	0.66	96.3	0.74

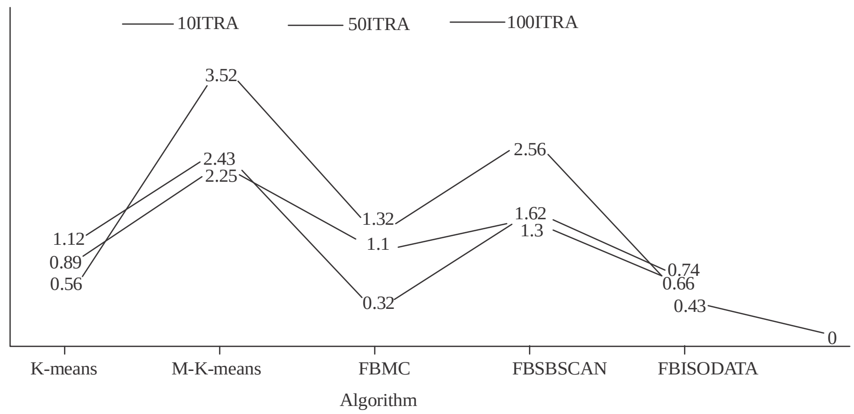

Fig. 7: Overall time period calcullation for the real time dataset (tiger image, data clustering with the existing and proposed methods on 10, 50 and 100 iterations (time period)

Figure 7 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, FBDBSCAN, FBISODATA and FBMC clustering. The accuracy chart is figurate on Table 1.

Figure 8 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 study proposes on four new clustering algorithm namely as M-k-means, FBDBSCAN (Fuzzy Based-Density Based Spatial Clustering With Application And Noise), 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 study. The proposed algorithms can execute and high performance result will be generated. The clustering result much effective and efficient process to be handle with the proposed algorithms. When compared the results a proposed methods. 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 and 92.3%, respectively and difference between these algorithms as 4% is k-means, 4.1% is M-k-means, 2.2% is FBDBSCAN and 0.1% is FBISODATA, these all algorithms comparing with FBMC and execution time is taken by the individually as 1.12 sec is k-means, 2.43 sec is taken by M-k-means, 0.32 sec is taken by FBMC, 1.62 sec is taken by FBDSCAN and 0.74 sec 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).

RECOMMENDATION

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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