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Automated Digital Image Clustering Algorithm Based on Colour Distance and IDBSCAN

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Abstract : Data clustering is inevitable for crucial data analytic based applications. Though data clustering algorithms are capacious in the literature, there is always a room for efficient data clustering algorithms. This is due to the uncontrollable growth of data and its utilization. The data clustering may consider any of the data formats such as text, images, audio, video and so on. Due to the increasing utilization trend of digital images, this work intends to present a data clustering algorithm for digital images, which is based colour distance and Improvised DBSCAN (IDBSCAN) algorithm. The proposed IDBSCAN completely weeds out the annoying process of setting the initial parameters such as ε and min_{pts} by setting them automatically. The performance of the proposed work is analysed in terms of clustering accuracy, precision, recall, F-measure and time consumption rates. The proposed work outperforms the existing approaches with reasonable time consumption.

Keywords : Digital image, clustering, DBSCAN, colour distance.

I. INTRODUCTION

Data analytics is an evergreen research area, which intends to analyse the vast amount of stored data in order to form knowledge patterns. The basic processes involved in data analysis are clustering and classification. The process of clustering works by grouping the related data entities together by examining the data. The clustering process does not require any prior knowledge. On the other hand, data classification intends to differentiate the data entities, such that they fall under a specific class. This activity requires prior training to the classification system. Hence, the clustering and classification processes are termed as unsupervised and supervised learning respectively.As the supervised learning requires adequate training for effective differentiation of data entities, unsupervised learning algorithms are employed for data analysis whenever decision making is not the case. The unsupervised learning is quite popular in different applications of data mining, digital image processing, pattern recognition and so on [1-4]. Basically, the clustering algorithms can be classified into four categories such as partitional, hierarchical, fuzzy, density and grid based clustering [5, 6]. Out of all these clustering algorithms, this work focuses on density based clustering, as this kind of clustering performs well in forming arbitrary shaped clusters and the spatial relationship between the data entities is also maintained.

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This work presents a clustering algorithm that operates on digital images. Owing to the increased utilization of image data, image analytics is the hot topic of research, as several applications such as biomedical, remote sensing, object detection, object recognition relies on digital images. Digital image clustering intends to group related image pixels under a single class, which makes it easy to distinguish between different areas available in an image. For instance in a medical image, the normal and abnormal areas (lesions or patches) can easily be differentiated by considering the nature of image pixels. Superpixel clustering algorithms are so popular these days and it clusters the image pixels with similar features. There are many superpixel clustering algorithms in the existing literature, however the main issues faced by them are clear edge, irregular shape, increased computational complexity and so on.Recognizing the benefits of density based clustering and superpixel clustering of images, this work intends to present an automated Density Based Spatial Clustering of Applications with Noise (DBSCAN) based superpixel clustering algorithm for digital images. DBSCAN is one of the most promising density based clustering algorithm, which can withstand noise, shapes and densities. However, the functionality of the DBSCAN algorithm completely relies on two parameters, which are ε (epsilon) and min_{pts} [5]. Epsilon is the radius from a corresponding pixel, which includes neighbouring pixels. When the corresponding pixel possesses required min_{pts} in the ε neighbourhood, then it is the core pixel. By this way, the clustering is done by DBSCAN algorithm and the main issue here is that the ε (epsilon) and min_{pts} are needed to be chosen manually.

The proposed superpixel clustering algorithm overthrows the need of manual choice of parameters involved in DBSCAN. Initially, the superpixels are formed with respect to colour and then the Improvised DBSCAN (IDBSCAN) algorithm is applied for refining the image clusters. The major contributions of this work are as follows.

- This work overthrows the requirement of the manual choice of ε (epsilon) and min_{pts} and the parameters are chosen automatically.
- The time complexity of the work is considerably reduced with better segmentation accuracy rates.
- The image pixels are clustered in two levels, where the first level of segmentation considers the colour information and the second level of segmentation is based on DBSCAN algorithm. This results in better clustering results.
- The proposed work can effectively cluster the image objects with irregular shape and size.

The remaining parts of the article are organized in the following format. Section 2 discusses the related literature with respect to superpixel clustering in digital images.

The proposed image clustering algorithm is presented in section 3 and the performance of the clustering algorithm is analysed in section 4. The article is concluded by section 5.

II. REVIEW OF LITERATURE

This section reviews the related literature with respect to superpixel clustering in image processing.

In [7], a superpixel segmentation scheme for polarimetric Synthetic Aperture Radar (SAR) imagery using local iterative clustering is proposed. This work utilizes the Simple Linear Iterative Clustering (SLIC) with improved the cluster centre point initialization. The experiments are carried out on SAR images.

An edge based superpixel similarity measurement scheme is presented in [8]. This work considers the edge spatial distribution by directional regions and these regions are employed to indicate the relationship between the superpixels and edges. The clustering of this work is performed by Directed Graph Clustering (DGC) and spectral clustering.

In [9], a method to compute content-sensitive superpixels is presented. This work improvises the SLIC clustering algorithm by computing content sensitive superpixels. In this paper, the smaller subpixels present in the dense regions with greater intensity or colour information and larger subpixels are considered. The Geodesic Centroidal Voronoi Tessellation (GCVT) induces the content sensitive superpixels.

A superpixel based fast fuzzy c means clustering algorithm is presented for color image segmentation in [10]. This work presents a superpixel based faster Fuzzy C Means (FCM) algorithm, which is based on multiscale morphological gradient reconstruction operation to form a superpixel image with better edges. The FCM algorithm is then applied on the superpixel image for the final clustered image.

In [11], an adaptive superpixel generation for SAR images based on linear feature clustering and edge constraints is presented. This work is based on three stages, which initially computes the local gradient ratio pattern of the pixel and the features are extracted. The feature ratio based edge detector with gauss shaped window is then utilized to obtain the edges. At last, a modified Normalized Cut (NCut) based superpixel clustering algorithm is presented.

A real-time superpixel segmentation algorithm based on DBSCAN algorithm is presented in [12]. This work clusters the images based on colour and spatial relationship and the clusters are joined together to form superpixels. In [13], a weakly supervised foreground segmentation technique based on superpixel grouping is proposed. This paper extracts the foreground objects from the complex background based on a predefined bounding box. This work utilizes watershed and mean-shift clustering algorithm to create superpixels.

An image segmentation algorithm based on superpixel clustering is presented in [14]. This work employs the superpixel pre-processing technique to split the image into several superpixel regions. The similarity matrix is then computed for clustering the superpixel regions and the result is obtained. The superpixel optimization technique based on higher order energy is proposed in [15]. This work employs k-means algorithm for forming initial superpixels. A higher order energy function is employed to detect the edges and regions.

In [16], a graph based segmentation for RGB-D data using three dimensional geometrical enhanced superpixel is presented. This work is based on two stages such as over-segmentation and graph-based merging. The three dimensional geometrical information is formed by using the depth map and the k-means algorithm is applied for over-segmentation. The graph based merging considers the superpixels as nodes and the correlation between the superpixels is determined.

In [17], a Superpixel Tensor Sparse Coding (STSC) based hyperspectral image classification scheme is presented. This work is based on the high order structure of hyperspectral image and the image is clustered into several superpixel tensors by means of hierarchical spatial affinity propagation algorithm. Finally, an STSC based classifier is presented for differentiation.

An unsupervised approach is presented to select the band of hyperspectral image in [18]. Initially, the spectral channels are identified by the superpixel and chunklets that are suitable for classifying between the land cover classes. A sequence of band criteria are then detected by means of optimal band transformation based on within-class and total variability. The acquired band measures are passed as an input to clustering algorithm.

In [19], a new technique to detect salient objects based on appearance comparison of superpixels of different sizes. The superpixels are formed by multivariate normal distributions and the Wasserstein distance is then computed to detect the similarity. The global saliency is measured to group pixels that appear similar visually and the locally constrained random walk technique is applied to detect the local similarity and saliency degrees.

A salient object segmentation technique is presented in [20], which is based on saliency, superpixel and background connectivity. Initially, the superpixels are formed out of an image with the help of SLIC algorithm and the background connectivity is applied to detect the spatial layout of the superpixel concerning the boundary. Finally, both the saliency and background connectivity are considered to form superpixels.

In [21], a change detection technique is presented on the basis of multiscale superpixel segmentation and stacked denoising encoders. The stacked denoising encoders are applied to infer about the difference in bi-temporal superpixels. Finally, the results are tuned by back propagation approach to classify between the changed and unchanged objects. In [22], an enhanced superpixel segmentation approach based on new similarity measure is presented on the basis of Ng-Jordan-Weiss (NJW) approach. The NJW measure is applied to cluster the superpixels and the similarity is measured by the kernel fuzzy similarity measure.

A simple algorithm to carry out superpixel clustering with respect to boundary constraint is presented in [23]. This work is based on a similarity measure that could balance between the edge details and compactness of the clusters. The seed positions of the superpixels are initialized and the initial pixel labels are obtained. The superpixels are then optimized on the basis of three-sigma rule.

Inspired by these existing works, this article intends to present an automated DBSCAN based superpixel clustering algorithm for digital images, which can preserve the edge and local properties of an image.

III. PROPOSED AUTOMATED DBSCAN BASED SUPERPIXEL CLUSTERING ALGORITHM

This work presents a DBSCAN based superpixel clustering algorithm, which is not constrained to any specific shape, while conserving the spatial relationship between the pixels. Owing to the efficiency of DBSCAN algorithm, the proposed clustering algorithm exploits DBSCAN algorithm and improvises the same.

The improvisation focuses to eliminate human intervention in choosing initial parameters such as ε and min_{pts}. The proposed work performs the clustering operation in two steps. Initially, the clusters are formed by considering colour information of the pixels and the clusters are refined by the proposed clustering algorithm. This idea increases the segmentation accuracy and can better handle irregular shaped objects as well. The overall flow of the work is depicted in figure 1.

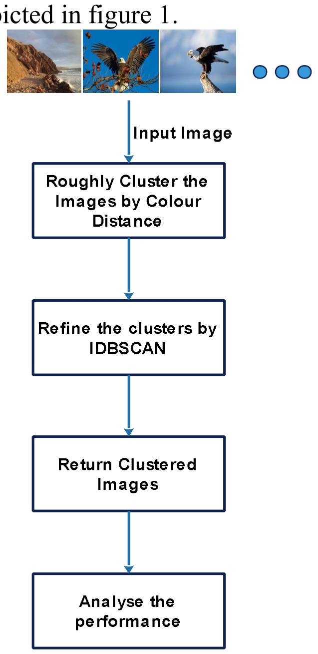

Fig.1. Overall flow of the work

Let the pixels be denoted as pix_i, where $i = (1,2,3, \ldots. n)$. For all the pix_i the coordinates (a_i, b_i) are obtained. As soon as the input image is passed, the initial level clustering operation is carried out by considering the colour information of the image pixels. The roughly clustered image is then treated with the clustering algorithm, which then refines the clusters with the help of IDBSCAN algorithm. Both the phases are explained in this section. As stated earlier, the initial clustering stage takes the colour information of the image pixels and the colour distance is measured.

$$CD_{xy} = \sqrt{(R_x - R_y)^2 + (G_x - G_y)^2 + (B_x - B_y)^2} \quad (1)$$

$$CD_{x1y1} = \sqrt{(R_{x1} - R_{y1})^2 + (G_{x1} - G_{y1})^2 + (B_{x1} - B_{y1})^2} \quad (2)$$

In the above equation, CD_{xy} is the colour distance between the image pixels x and y. R,G,B stands for the red, green and blue colour information of the pixels x and y. Hence, the colour distance between every two pixels is found out and a superpixel is formed, when the colour information of any two clusters is the same.

$$M_c = CD_{xy} + CD_{x1y1};\ if\ dis(CD_{xy}, CD_{x1y1})\ is\ minimal \quad (3)$$

By this way, the initial clusters are formed and then these rough clusters are passed on to the proposed automated IDBSCAN based image clustering algorithm, which is presented as follows.

The traditional DBSCAN algorithm is based on ε and min_{pts}, where min_{pts} indicate the least number of points to be under a cluster with ε as radius. The choice of min_{pts} must be optimal such that the smaller sized clusters can be created and the noise can be handled effectively. However, fixing these values is quite difficult manually and it involves more time. This issue is addressed by the proposed IDBSCAN algorithm, which fixes these values automatically. The overall algorithm of this work is presented as follows. The pixels of the roughly formed clusters are again extracted in order to ascertain better clusters with crispy edges. Mahalanobis distance (Dis) is computed between the pixels of the roughly formed clusters and the k-nearest neighbours are detected. Arrange the distance in ascending order, which starts from the least to the greatest distance, which makes it simple to detect the least possible distance between the pixels. For every available distance, count the neighbourhood pixels, which is represented by $Dis(TP)$. Here, TP is the total count of pixels. After this process, set the Mp, which is the min_{pts} by computing the mean of total neighbourhood pixels by considering all the distances, as represented in eqn.4.

$$mp = \sum_{i=1}^{n} \frac{i(TP)}{n} \quad (4)$$

In the above equation, mp stands for min_{pts}, i represents all the possible distances. $i(TP)$ indicates the total count of pixels in a specific distance i between the pixels. Now, all the distances (P_{dis}) with neighbourhood pixels greater than or equal to mp are detected.

$$P_{dis_i} = dis_i(TP) \geq mp \quad (5)$$

Now all the $P_{di\ i}$ are arranged in descending order and the distance with maximum pixels is set as ε.

$$\varepsilon = Max(P_{dis_i}) \quad (6)$$

Proposed Automated DBSCAN based Superpixel Clustering Algorithm

Input : Digital Images
Output : Clustered images
Begin
For all input images
Do
Compute the colour distance between the pixels by eqn.1;
Merge the pixels if the colour distance is minimal;
Extract the coordinates of all pixels in roughly formed clusters;
Compute mahalanobis distance to detect neighbourhood clusters;
Arrange the distances (Dis) *in ascending order;*
Find the least possible distance (LP_{dis}) *between the pixels;*
For all Dis
Compute the total count of neighbourhood pixels $C(p)$;
Compute the mean mp=A$(TC(p))$ *w.r.t Dis by eqn.(4);*
Set $min_{pts} = mp$;
Detect the Dis with minimally available min_{pts};
Set ε;
End for;
End Do;
End for;
End;

To summarize the proposed algorithm, the coordinates of all the pixels in the roughly formed clusters are obtained and the Mahalanobis distance is computed to find the k-nearest neighbourhood clusters. The distances between the image pixels are sorted in ascending order for detecting the least available distance between the pixels. The neighbourhood pixels of every corresponding pixel are computed by considering all the distances. The total counts of neighbourhood pixels for all distances are taken into account and the average is computed.

The so computed average value is set as min_{pts}, which is represented as mp. Detect the distance at which the least mp points in a cluster. Set the value of ε with the maximal possible distance containing pixels equal to or more than mp. The finally formed clusters are in arbitrary shape and do not follow any shape constraints. Suppose, when a pixel does not come under any cluster, then it is considered as noise. Additionally, the proposed algorithm eliminates the requirement to manually fix the ε and min_{pts} by automatic optimal choice of the parameters. The performance of the proposed work is evaluated in the following section.

IV. RESULTS AND DISCUSSION

The proposed automated DBSCAN based superpixel clustering algorithm is simulated in Matlab 2016B environment on a stand alone computer with 8 GB RAM and with i7 processor. The performance of the proposed algorithm is analysed upon the standard benchmark clustering dataset 'Berkeley segmentation dataset' [24], which contains about five hundred images with size 321×481.

Some of the sample images are shown in figure 2. The performance of the proposed work is compared with the existing approaches such as binary edge map [8], fast FCM based [10], similarity matrix based [14] and spectral clustering based [22]. The results attained by the proposed work are evaluated in terms of standard performance metrics such as accuracy, precision, recall, F-measure and time consumption.

Segmentation or clustering accuracy is the most important metric, which indicates the exactness of the proposed clustering algorithm. When the proposed work is considered, the segmentation accuracy implies the perfect segmentation of the image regions with preserved edges. The segmentation accuracy rates are computed by the following equation.

$$A_r = \frac{TP+TN}{TP+TN+FP+F} \times 100 \quad (7)$$

In the above equation, TP, TN, FP and FN indicate the true positive, true negative, false positive and false negative rates. Precision and recall are the other two important metrics, which determine the effectiveness of clustering. Greater precision and recall rates indicate that the right pixels are clustered together. Grouping of dissimilar pixels results in minimal precision and recall rates. The terms TP and TN indicate that only the similar pixels are grouped under a cluster and the dissimilar pixels are rejected from being a part of a cluster respectively.

FN rates increase when the clustering algorithm declares a similar pixel as dissimilar. The precision and recall rates are closely associated with the FN and FP rates respectively. When the FN rates increase, the precision rate of the clustering algorithms falls. In the same way, the recall of the clustering algorithm increases, when the FP rates are reduced. The precision and recall of the proposed approach are computed by

$$P_r = \frac{TP}{TP+} \times 100 \quad (8)$$

$$R_r = \frac{TN}{TN+F} \times 100 \quad (9)$$

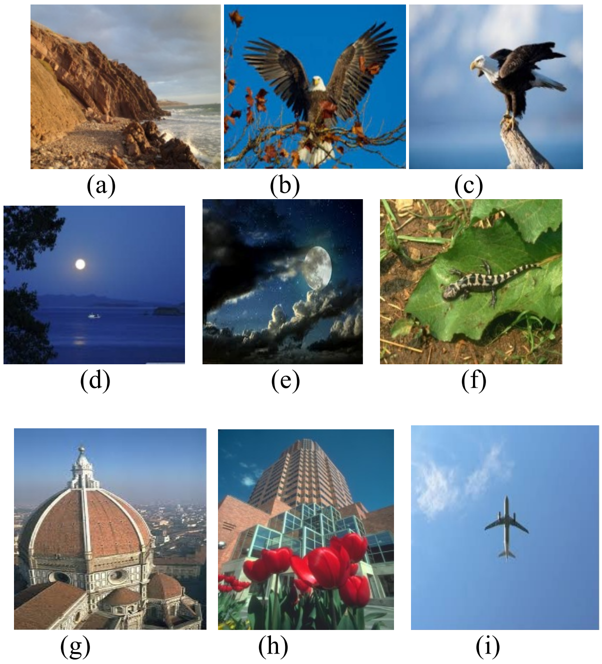

Fig.2. (a-i) Sample input images

The F-measure rate relies on the precision and recall rates of the clustering algorithm, which is computed by the following equation. The greater the precision and recall rates, the greater is the F-measure rate.

$$F_r = \frac{2*P_r*R_r}{P_r+R_r} \quad (10)$$

The visual results attained by the classic DBSCAN and the proposed IDBSCAN clustering algorithms are shown in figures 3 and 4.

Fig.3. (a-i) Clustering results by the traditional DBSCAN

The figure 3 shows the sample clustering results with traditional DBSCAN, which does not cluster the pixels perfectly and the shape of superpixel is not even. The main reason for the poor clustering is the poor choice of epsilon and minimum points.

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Hence, the user must have sufficient knowledge about the dataset and the algorithm, only then the reasonable clustering results can be obtained. In order to deal with this issue, the proposed work presents IDBSCAN which automatically chooses the initial parameters of the algorithm and this leads to better results. The clustering results are shown in figure 4.

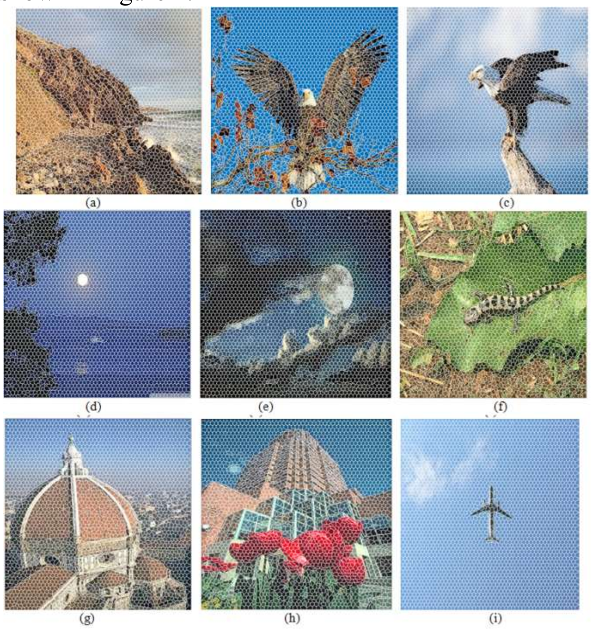

Fig.4. (a-i) Sample clustering results by the proposed clustering algorithm

From the visual results, it is obvious that the proposed work effectively clusters the objects present in the images. The performance of the proposed work is stable even for images with complex background and thinner edges. Besides, the proposed clustering algorithm shows regular and compact superpixels and the results are produced in a reasonable period of time.

The following section shows the results attained by the proposed work in terms of accuracy, precision, recall, F-measure and time consumption. The performance of the work is tested in two rounds, in which the first round justifies the combination of colour and DBSCAN clustering. Secondly, the performance of the work is compared with existing approaches and the results are summarized.

4.1 Performance Analysis w.r.t Clustering Techniques

The proposed work performs clustering operation in two phases. Initially, the pixels are roughly clustered by the colour distance between the pixels and then the IDBSCAN algorithm is applied. This section intends to justify the combination of both the clustering phases. The results are taken by incorporating the colour distance alone for clustering, IDBSCAN alone, colour distance + IDBSCAN. The performances of all these techniques are shown in the following table.

Table 1. Experimental Results

Perf.Metrics	Colour Distance alone	IDBSCAN alone	Colour distance + IDBSCAN
Accuracy (%)	71.2	86.2	98.2
Precision (%)	68.3	83.1	96.7
Recall (%)	62.4	79.8	93.9
F-measure (%)	65.21	81.41	95.28
Time consumption (ms)	768	1136	1496

The colour distance can complement the IDBSCAN algorithm well however, it can perform better individually. This is because, the colour information of the pixels alone are considered, irrespective of any textural patterns and shape information.

Thus, the results are not convincing. The proposed clustering algorithm performs better due to the inclusion of both colour distance and IDBSCAN based clustering. This idea shows better clusters at the cost of reasonable time consumption. The following section shows the comparative analysis of the proposed work with the existing approaches.

4.2 Comparative Analysis with Existing Approaches

This section compares the work performance of the proposed clustering algorithm with the existing approaches such as binary edge map [8], fast FCM based [10], similarity matrix based [14] and spectral clustering based [22]. The experimental results attained by the proposed clustering algorithm in terms of accuracy, precision, recall, F-measure and time consumption are presented in the following figures 4 and 5.

The clustering accuracy, precision and recall rates are greater, which implicitly states that the proposed work performs the clustering operation effectively with reduced FP and FN rates. Inclusion of a dissimilar pixel under a cluster or eliminating a similar pixel from a cluster results in increased FP or FN rates. The greater precision and recall rates lead to better F-measure rates as well.

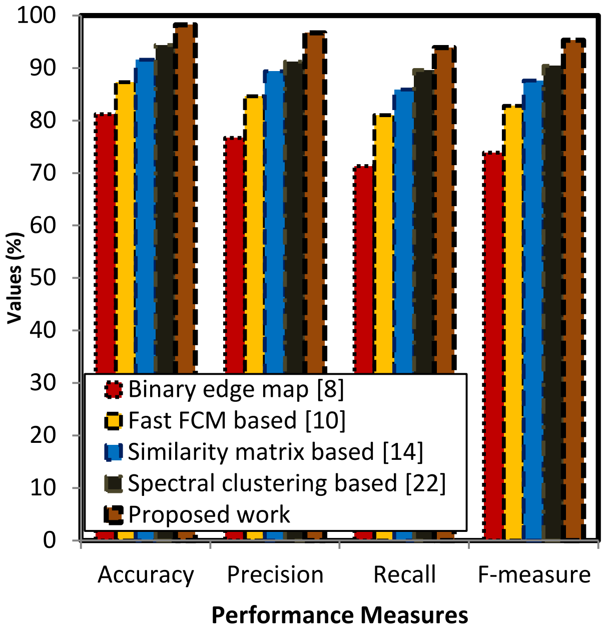

Fig.5. Comparative analysis with existing approaches

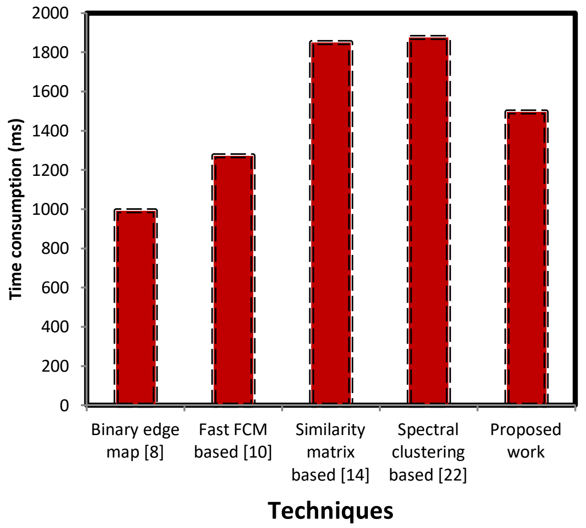

Fig.6. Time consumption analysis

The proposed work shows better results at the cost of reasonable time consumption, which better than some existing techniques. However, the performance of the proposed clustering algorithm is greater than the existing clustering approaches. From the experimental analysis, it is observed that the clustering performance of the proposed work is satisfactory, while consuming reasonable time consumption. The paper is concluded by the following section.

V. CONCLUSIONS

This article presents a clustering algorithm for digital images, which is based on colour distance similarity and IDBSCAN algorithm. Initially, the images are clustered roughly with respect to the colour information of the pixels. The roughly clustered images are then treated by IDBSCAN, which is an improvised version of traditional DBSCAN algorithm.

The IDBSCAN algorithm eliminates the need of setting the parameters such as ε and min_{pts} manually and sets the parameters automatically. This idea frees the users from setting the optimal values of the parameters, which have a direct impact on the clustering performance. The clustering outcome of the proposed work is regular and consistent.

The performance of the proposed clustering algorithm is compared with the existing approaches and the proposed work proves better results. In future, this work is planned to be extended, such that it can deal with 3D images.

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