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Compression of Color Images Using Clustering Techniques

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Abstract— This paper deals mainly with the image compression algorithms and presents a new color space normalization (CSN) technique for enhancing the discriminating power of color space along with the principal component analysis (PCA) which enables compression of colour images. Context-based modeling is an important step in image compression. We used optimized clustering algorithms to compress images effectively by making use of a large number of image contexts by separating a finite unlabeled data set into a finite and discrete set of natural, hidden data structures, rather than provide an accurate characterization of unobserved samples generated from the same probability distribution. Since images contain large number of varying density regions, we used an optimized density based algorithm from a pool. PCA is used to express the large 1-D vector of pixels constructed from 2-D color image into the compact principal components of the feature space. Each image may be represented as a weighted sum (feature vector) of the eigen values, which are stored in a 1D array. PCA allows us to compute a linear transformation that maps data from a high dimensional space to a lower dimensional space. It covers standard deviation, covariance, eigen vectors and eigen values. These values are provided at the compression side. So the decompressed image has not much loss of information. Experiments using different databases show that the proposed method by combining color space discrimination and PCA can improve compression of color images to a great extend.

Index Terms— Color model, Color Space, Color Space normalization, Context Modeling, Prediction by Partial Approximate Matching(PPAM), Principal Component Analysis,Varied Density Based Clustering Applications with Noise(VDBSCAN).

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1 Introduction

IMAGE compression is minimizing the size in bytes of a graphics file without degrading the quality of the image to an unacceptable level. The reduction in file size allows more images to be stored in a given amount of disk or memory space. It also reduces the time required for images to be sent over the Internet or downloaded from Web pages. There are several different ways in which image files can be compressed. All compression techniques abbreviate the string of binary code in an uncompressed image to a form of mathematical shorthand, based on complex algorithms. .In image compression, a small loss in quality is usually not noticeable. The objective of image compression is to reduce the redundancy of the image data in order to be able to store or transmit data in an efficient form. Most successful image compression algorithms, are, however context based and they exploit the 2-D spatial redundancy in natural images [2]. Examples include LJPG (lossless JPEG), FELICS [4], CALIC [6], [7], JPEG-LS [8], TMW [9]. These methods usually involve four basic components [1].

FELICS, which stands for Fast Efficient & Lossless Image Compression System, is a lossless image compression algorithm that performs 5-times faster than the original lossless JPEG codec. Like other lossless codecs for continuous-tone images, FELICS operates by decorrelating the image and encoding it with an entropy coder. The decorrelation is the context $\Delta = H - L$ where $H = max(P1,P2)$ and $L = min(P1,P2)$ where $P1,P2$ are the pixel's two nearest neighbors coded used for providing the context to code the present pixel P. CALIC is basically a variation on a few well known methods namely predictive coding, context based selection of predictor co-efficients and a fading memory model for prediction error distributions.

TMW is based on the use of linear predictors and implicit segmentation. The compression process is split into an analysis step and a coding step. In the first step, a set of linear predictors and other parameters suitable for the image is calculated, which is included in the compressed file and subsequently used for the coding step. This adaption allows TMW to perform well over a very wide range of image types.

Lossless image compression scheme contains following components – a predictive model, a context selection strategy, a context modeling scheme and an encoder. An initial prediction scheme to remove the spatial redundancy between neighboring pixels. The major challenge is the development of an accurate predictive model, i.e., how to fully exploit the information contained in the context to resolve the uncertainty of X(n) . LS-based approaches locally optimize the prediction coefficients inside a causal window. A convenient choice of the training window is the double-rectangular window, which contains causal neighbors M=2T(T+1). The effectiveness of any adaptive prediction scheme depends on its capability of adapting from smooth regions to edge areas.

A context selection strategy for a given position in the image; a modeling method for the estimation of the conditional probability distribution of the prediction error given the context in which it occurs. The full information contained in the data as specified by the probability density function. The set of past observations on which the probability of the current symbols is conditioned is called the modeling context. The resulting code length will increase despite the fact that conditioning reduces entropy [9]. To deal

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with the model cost, various schemes were proposed. Tree structures are applied to represent the context model. The model cost is reduced by pruning the tree to form an optimum tree or by weighting the probabilities of the descendents of the tree root. Meanwhile, the quantization of the context events is an important technique to reduce the model cost while retaining most of the context information. In the context, variable is quantized to reduce the number of parameters in the context model.

If we can find the optimal quantization value for a given partition, the context quantization can also be implemented by an iterative algorithm. This means context quantization increases entropy. However, context quantization reduces the model cost at the same time. By applying a properly designed context quantizer, better compression performance can be achieved by an arithmetic coder with the quantized context. The optimization objective of the context quantization becomes: for a given number of quantization levels, K, K>N find an optimum partition scheme for ei,i=1…N then calculate the optimum quantization values Q(P(c/ei)for all partitions K so that the distortion (6) is minimized. The optimality of context quantization is defined to be the minimum static or minimum adaptive code length of given a data set**.**

In PPAM [1] the contexts are selected in such a way that each pair of corresponding positions does not exceed the error bound. This algorithm starts with exact matches, and search for 0-approximate contexts. If the number of 0-approximate contexts is smaller than a predetermined threshold, is incremented by 1, and the search restarts with the new value. This process continues until enough number of approximate contexts or reaches a maximum allowable error. The statistics obtained are then used to estimate the conditional probability distributions for the symbols.

Thus, in PPAM, when the approximate context is not found, rather than escaping to a lower order context as in PPM, it make a transition to the next higher value of order. Hence, there is no need to send escape symbols, since the decoder can repeat the same search steps as the encoder.

To search for approximate contexts efficiently, PPAM stores the contexts that have been previously observed in a PPAM context tree. This is simply a balanced binary search tree, where each node is augmented with five parameters. For images, the number of high-order contexts could be quite large. The number of contexts increases with increasing value of the error parameter. This leads to a time consuming process for context searching and requires a considerable amount of memory for storage.

PPAM [1] uses square of Euclidian distance metric to cluster images based on a reference context. The SED value is a non-negative integer and, thus, can be used as an index for the context. Contexts with the same SED values are then grouped into the same partition. Then for a given partition, estimate a probability distribution for the symbols and store one probability value for each quantization partition.

In lossless image compression, pixel prediction is often performed before entropy coding. Thus, the overall performance of an image coding scheme will be significantly influenced by the prediction algorithm used. Context searching and quantization are also applied on the prediction errors rather than the pixel values. To maximize compression, can be estimated based on the residue image, and then stored as part of the compressed bit stream.

Cluster Analysis, an automatic process to find similar objects from a database, is a fundamental operation in data mining. A cluster is a collection of data objects that are similar to one another within the same cluster and are dissimilar to the objects in other. Clustering analysis is a primary method for data mining. Clustering is the process of allocating points in a given dataset into disjoint and meaningful clusters. There are five areas of clustering, which are Partitioning, Hierarchical, Density, Grid, and Model methods.

Density clustering methods are very useful to find clusters of any shape, giving the correct parameters . Roughly speaking, the goal of a clustering algorithm is to group the objects of a database into a set of meaningful subclasses. DBSCAN (Density Based Spatial Clustering of Applications with Noise) is a traditional and widely-accepted density-based clustering method. It can find clusters of arbitrary shapes and sizes yet may have trouble with clusters of varying density. The density-based algorithms still suffer from several problems. Traditional algorithms, such as DBSCAN can have trouble with density if the density of clusters varies widely. To resolve the problem of DBSCAN, VDBSCAN is introduced for the purpose of effective clustering analysis of datasets with varied densities. It selects suitable parameters for different density, using k-dist plot, and adopts DBSCAN algorithm for each chosen parameter.

Different color spaces derived from different transformations of the RGB color space revealed different performance. The YUV color space, for example, is shown more effective than the RGB color space. The YQCr color configuration (a hybrid color space), where the Y and Q color components are from the YIQ color space and the Cr color component is from theYCbCr color space, is more powerful than the RGB, HSV and L a*b* color spaces. Another two hybrid color spaces, RIQ, RQCr are demonstrated effective recently. Some color spaces generated by evolution algorithms and discriminant models also turn out to be very powerful. Current research findings showed that some linear color spaces, which are derived by linear transformations from the RGB color space, perform much better those derived by nonlinear transformations from the RGB color space. We therefore focus on linear color spaces in this paper. Rather than searching for a more effective color space, we try to explore general ways for enhancing the performance of conventional color spaces for compressing images [15].

While assessing the performance of different color spaces using a large scale database, some color spaces such as RGB, XYZ, HSV and L*a*b* are relatively weak where as the others, such as I1I2I3, YUV, YIQ and LSLM are relatively powerful in achieving good performance. By analyzing the transformation matrices of the I1I2I3, YUV, YIQ and LSLM color spaces, we find out that these matrices all share a common characteristic: the sum of the elements in the second and third rows of the transformation matrix are both zero. The RGB and XYZ color spaces [17], however, do not have such a property. Inspired by the finding of the difference of the transformation matrices between the weak and the powerful color spaces, we present the concept of color space normalization (CSN) and develop two CSN techniques. These CSN techniques normalize any color space that is derived by a linear transformation of the RGB color space, so that the normalized color space possesses the same properties as the powerful color spaces do. The proposed two techniques are demonstrated to be very effective: the normalized RGB and XYZ color spaces are as powerful as or even powerful than I1I2I3, YUV, YIQ and LSLM color space [15].

Previous color space selection is limited to set of conventional color spaces or their hybrids. Specifically, we choose a powerful color space by experiments from the two set of hybrid color spaces that are generated by choosing some color components from the conventional color spaces. The weak color spaces are simply left behind unsatisfactory performance. The proposed color space normalization techniques, however, can convert the weak color spaces into powerful ones, and these normalized color spaces form a new set of color spaces, from which we might find a more effective color space for compression task [16]. The three sets of color spaces are illustrated in the Fig. 1.

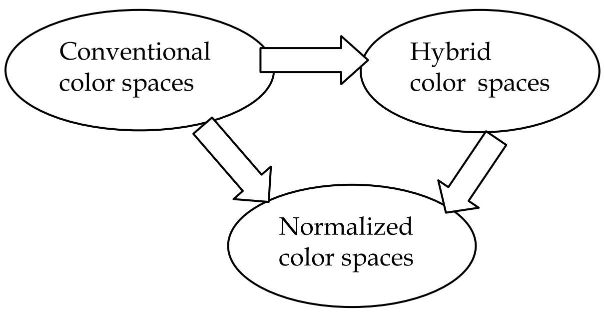

Fig 1. Color Spaces

The paper presents compression of color images using clustering techniques. Section 1 gives an introduction about the image compression, the clustering techniques, different color spaces and normalization of color spaces. It also gives description about the organization of the paper. Section 2 provides an overview of the proposed algorithm. Section 3 gives the implementation details and the results of the proposed color image compression using clustering techniques. The conclusion of the proposed algorithm is explained in section 4.

2 Proposed Algorithm

2.1 Color Spaces

The RGB color space is a fundamental and commonly used color space. Other Color spaces can be calculated from the RGB color space by means of either linear or nonlinear transformations. It is apparent that every color space derived by the linear transformation of the RGB color space is uniquely determined by the associated transformation matrix. In the following, we review five color spaces derived from the RGB color space via linear transformations [17].

The XYZ color space was derived from a series of experiments in the study of the human perception by the International Commission on Illumination (CIE) in 1931. The transformation from the RGB color space to the XYZ is as follows:

$$\begin{bmatrix} X \\ Y \\ Z \end{bmatrix} = \begin{bmatrix} 0.607 & 0.174 & 0.201 \\ 0.299 & 0.587 & 0.114 \\ 0.000 & 0.066 & 1.117 \end{bmatrix} \begin{bmatrix} R \\ G \\ B \end{bmatrix} \quad (1)$$

The I1I2I3 color space was obtained through the decorrelation of the RGB color components using K-L transform by Ohta et al. in 1980. The transformation from the RGB color space to the I1I2I3 color space is as follows:

$$\begin{bmatrix} I_1 \\ I_2 \\ I_3 \end{bmatrix} = \begin{bmatrix} 1/3 & 1/3 & 1/3 \\ 1/2 & 0 & -1/2 \\ -1/2 & 1 & -1/2 \end{bmatrix} \begin{bmatrix} R \\ G \\ B \end{bmatrix} \quad (2)$$

The YUV color space is defined in terms of one luminance (Y) and two chrominance components (U and V), and is used in the PAL (Phase Alternating Line), NTSC (National Television System Committee), and SECAM (Sequential Couleur a memoire) composite color video standards. The transformation from the RGB to the YUV color space is as follows:

$$\begin{bmatrix} Y \\ U \\ V \end{bmatrix} = \begin{bmatrix} 0.2990 & 0.5870 & 0.1140 \\ -0.1471 & -0.2888 & 0.4359 \\ 0.6148 & -0.5148 & -0.1000 \end{bmatrix} \begin{bmatrix} R \\ G \\ B \end{bmatrix} \quad (3)$$

The YIQ color space was formerly used in the National Television System Committee (NTSC) television standard. The YIQ system, which is intended to take advantage of human color response characteristics, and can be derived from the corresponding RGB space as follows:

$$\begin{bmatrix} Y \\ I \\ Q \end{bmatrix} = \begin{bmatrix} 0.2990 & 0.5870 & 0.1140 \\ 0.5957 & -0.2744 & -0.3213 \\ 0.2115 & -0.5226 & -0.3111 \end{bmatrix} \begin{bmatrix} R \\ G \\ B \end{bmatrix} \quad (4)$$

The I and Q components in the YIQ color space are obtained via clockwise rotation (33 degree) of the U and V color components in the YUV color space.

The LSLM color space is a linear transformation of the RGB color space based on the opponent signals of the cones: black-white, red-green and yellow-blue. The LSLM color space is defined as follows:

$$\begin{bmatrix} L \\ S \\ LM \end{bmatrix} = \begin{bmatrix} 0.209 & 0.715 & 0.076 \\ 0.209 & 0.715 & -0.924 \\ 3.148 & -2.799 & -0.349 \end{bmatrix} \begin{bmatrix} R \\ G \\ B \end{bmatrix} \quad (5)$$

2.2 Color Space Normalization Concept and techniques

Different color spaces usually display different discriminating power.Some color spaces, such as the RGB and XYZ color spaces , are relatively weak, where as other color spaces, such as the I1I2I3, YUV, YIQ and LSLM color spaces ,are relatively

powerful because of the sums of the elements in the second and third rows of the transformation matrix are both zero. The RGB and XYZ color spaces, however, do not have such a property.
The transformation matrix of the RGB color space is an identity matrix:

$$\begin{bmatrix} R \\ G \\ B \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & O \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} R \\ G \\ B \end{bmatrix} \quad (6)$$

The CSN techniques normalize any color space that is derived by a linear transformation of the RGB color space, so that the normalized color space possesses the same property as the powerful color spaces do, i.e., the sums of the elements in the second and third rows of the transformation matrix are both zero.

2.3 Within Color component Normalization

To achieve the goal that the sums of the elements in the second and the third rows of the color space transformation matrix are zero, the within-color-component normalization technique works by directly removing the means of the second and third row vectors, respectively. Let C_1, C_2 and C_3 be the three color components derived by the following linear transformation of RGB color space:

$$\begin{bmatrix} C_1 \\ C_2 \\ C_3 \end{bmatrix} = A \begin{bmatrix} R \\ G \\ B \end{bmatrix} = \begin{bmatrix} A_1 \\ A_2 \\ A_3 \end{bmatrix} \begin{bmatrix} R \\ G \\ B \end{bmatrix} = \begin{bmatrix} a_{11} & a_{12} & a_{13} \\ a_{21} & a_{22} & a_{23} \\ a_{31} & a_{32} & a_{33} \end{bmatrix} \begin{bmatrix} R \\ G \\ B \end{bmatrix} \quad (7)$$

The mean of the second row vector of the transformation matrix A is $m_2= (a_{21}+a_{22}+a_{23})/3$ and the mean of the third row vector is $m_3= (a_{31}+a_{32}+a_{33})/3$. Removing m_2 from the second row vector and m_3 from the third row vector, we obtain a normalized transformation matrix A_I, which determine the normalized color space: $C_1\ C_2\ C_3$:

$$\begin{bmatrix} \breve{C}_1 \\ \breve{C}_2 \\ \breve{C}_3 \end{bmatrix} = \breve{A}_1 \begin{bmatrix} R \\ G \\ B \end{bmatrix} = \begin{bmatrix} A_1 \\ \breve{A}_2 \\ \breve{A}_3 \end{bmatrix} \begin{bmatrix} R \\ G \\ B \end{bmatrix} \begin{bmatrix} a_{11} & a_{12} & a_{13} \\ a_{21}-m_2 & a_{22}-m_2 & a_{23}-m_2 \\ a_{31}-m_3 & a_{32}-m_3 & a_{33}-m_3 \end{bmatrix} \begin{bmatrix} R \\ G \\ B \end{bmatrix} \quad (8)$$

The within-color-component normalization technique is named color space normalization1 (CSN-1). The normalized RGB color space using CSN-1 is

$$\begin{bmatrix} \breve{R}_1 \\ \breve{G}_2 \\ \breve{B}_3 \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 \\ -1/3 & 2/3 & -1/3 \\ -1/3 & -1/3 & 2/3 \end{bmatrix} \begin{bmatrix} R \\ G \\ B \end{bmatrix} \quad (9)$$

The normalized XYZ color space using CSN-I is

$$\begin{bmatrix} \breve{R}_1 \\ \breve{G}_2 \\ \breve{B}_3 \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 \\ -1/3 & 2/3 & -1/3 \\ -1/3 & -1/3 & 2/3 \end{bmatrix} \begin{bmatrix} R \\ G \\ B \end{bmatrix} \quad (10)$$

2.4 Across color Component Normalization

To make the sums of these elements in the second and third rows of the color space transformation matrix is zero, the across-color-component normalization technique works in the following way. The original three row vectors of the color space transformation matrix are first used to generate two zero-mean row vectors via a linear combination. A new color space transformation matrix is then obtained by replacing the second and third row vectors of the original transformation matrix with the generated two zero-mean row vectors. The linear combination of the three row vectors of the original color space transformation matrix A may be written as follows:

$$\xi = K_1A_1 + K_2A_2 + K_3A_3 = \left(\sum_{i=1}^{3} k_i a_{i1}, \sum_{i=1}^{3} k_i a_{i2}, \sum_{i=1}^{3} k_i a_{i3}\right) \quad (11)$$

Let the sum of the elements of this linear combination vector ξ (row vector) be zero, i.e.,

$$\begin{aligned} \sum_{i=1}^{3} k_i a_{i1}, \sum_{i=1}^{3} k_i a_{i2}, \sum_{i=1}^{3} k_i a_{i3} &= \sum_{j=1}^{3} k_{1\,+}\, a_{1j} \sum_{j=1}^{3} k_{2\,+}\, a_{2j} \sum_{i=1}^{3} k_{3\,+}\, a_{3j} \\ &= [s_1, s_2, s_3][k_1, k_2, k_3]^T = 0 \end{aligned} \quad (12)$$

Where $s_i = \sum_{j=1}^{3} a_{ij}$, i=1, 2,3. Obviously, si is the sum of the elements of the i th row vector of the color space transformation matrix A.

The previous equations shows that the linear combination coefficient vector $[k_1, k_2, k_3]^n$ can be chosen as the basis vectors of the null space of $[s_1, s_2, s_3]$. Since this null space is two-dimensional, it has only two basis vectors. Let the two basis vectors be $K_1= [k_{11}, k_{21}, k_{31}]^n$.
The normalized color space transformation matrix is defined as follows:

$$\breve{A}_{II} = \begin{bmatrix} A_1 \\ \xi_1 \\ \xi_2 \end{bmatrix} \quad (13)$$

which determines the following normalized color space C1C2C3:

$$\begin{bmatrix} \breve{C}_1 \\ \breve{C}_2 \\ \breve{C}_3 \end{bmatrix} = \breve{A}_{II} \begin{bmatrix} R \\ G \\ B \end{bmatrix} \quad (14)$$

By applying these methods first we find out normalized color space of the input image .This will be the input of the compression procedure.

2.5 Compression using Clustering

This algorithm exploits the potentially large number of similar contexts and other special characteristics of natural images. The proposed algorithm [14] selects some biased points in the normalized color image which is set as the center of clusters. Then calculate the distance of each pixel value in the image from the biased points. The average distance of all pixels in the image from these biased points are calculated for each selected point and draw a cluster by taking these points as centers and radius as the average distance. Then find out the nearest pixels of each cluster and find out their relative position. Then calculate number of repetition of each selected point. Then sort the points and find out the position where a drastic change appears. Then label all points as border, noise or core. Eliminate noise points. Draw a line between core points which are Eps distance away from each other. Make each group of connected core points in to separate cluster. Assign each border point to one of the clusters with its associated core point. Give Id to each cluster. This will be the output after compression. To decompress there is mapping between cluster ID and biased points selected for clustering which is applied.

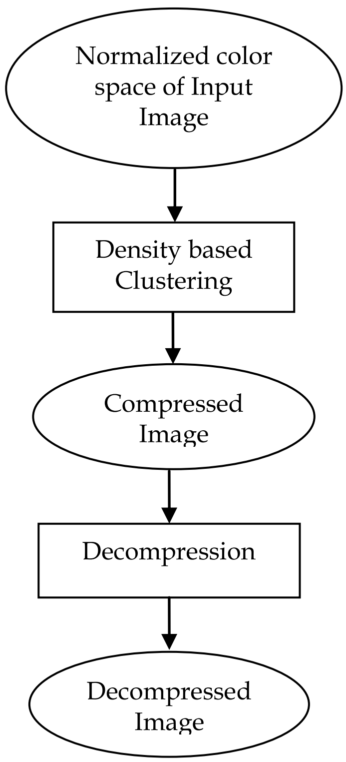

Fig. 2 Compression and Decompression Procedure

Density clustering methods are very useful to find clusters of any shape, giving the correct parameters. DBSCAN is a traditional accepted density-based clustering method. It can find clusters of arbitrary shapes and sizes yet may have trouble with clusters of varying density. Traditional algorithms can have trouble with density if the density of clusters varies widely. To resolve the problem of DBSCAN, VDBSCAN is introduced for the purpose of effective clustering analysis of datasets with varied densities. It selects suitable parameters for different density, using k-dist plot, and adopts DBSCAN algorithm for each chosen parameter.

DBSCAN algorithm [11] is based on centre-based approach. In the centre-based approach, density is estimated for a particular point in the dataset by counting the number of points within a specified radius, Eps, of that point. This includes the point itself. The centre-based approach to density allows us to classify a point as a core point, a border point, a noise or background point. A point is core point if the number of points within Eps, a user-specified parameter, exceeds a certain threshold, MinPts, which is also a user specified parameter. Any two core points that are close enough within a distance Eps of one another are put in the same cluster. It is also applicable for any border point which is close enough to a core point is put in the same cluster as the core point. Noise points are disposed.

VDBSCAN algorithm calculates and stores k-dist for each and partition k-dist plots. Then the number of densities is given intuitively by k-dist plot. Choose parameters *Epsi* automatically for each density. Scan the dataset and cluster different densities using corresponding Epsi. Finally, display the valid clusters corresponding with varied densities. VDBSCAN has two steps: choosing parameters Epsi and cluster in varied densities.

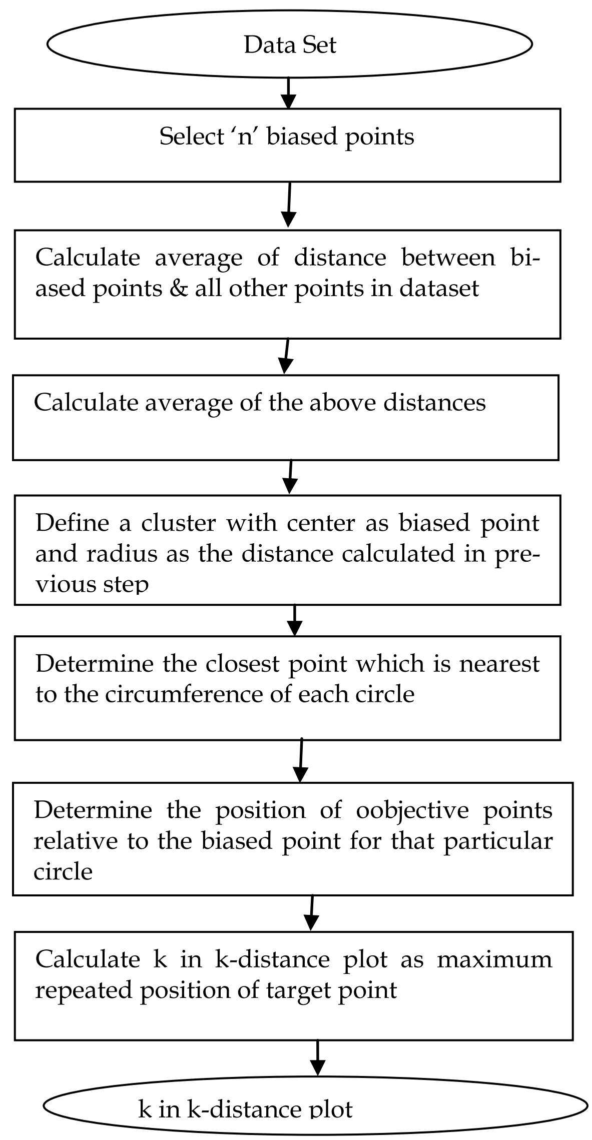

Fig. 3 Procedure for Calculating Parameter k

3 Implementation and Experimental Result

The algorithm is evaluated using several still color image databases. The database for image compression is constructed from JPEG2000, the World Wide Web, and personal photo collections. These images have been taken with complex backgrounds.

Database includes images of arbitrary shapes, colours and large number of varying contexts. So we implemented density based clustering method and color space normalization to compress such images. Density clustering methods are very useful to find clusters of any shape. In this approach, a cluster is regarded as a region in which the density of data objects exceeds a threshold. Here we implemented modified VDB-SCAN [13] for the purpose of effective clustering analysis of datasets with varied densities. It selects suitable parameters for different densities, using k-dist plot. This algorithm successfully compressed a large number of images with any shapes, colors and densities. Further, the algorithm improves the quality of output images by reducing the noise components. It also enhances the compression ratio.

The database contains 121 images. After analyzing the algorithm using this database, it is found that the overall performance is good. All the algorithmic parameters demonstrate that our algorithm can successfully compress wide range of color images. Fig. 5 shows the results after applying the algorithm on Fig. 4

Fig. 4. Input Image

Fig. 5. Decompressed Image

4 Conclusion

This paper presents the concept of compression of color images using clustering techniques. The proposed compression technique is applied to the images of arbitrary shapes and large number of varying contexts. All experimental results demonstrated the effectiveness of the proposed technique. This algorithm successfully compressed a large number of images with any shapes, color and densities. Further, the algorithm enhances the PSNR value of decompressed images as well as the compression ratio.

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