Image Information Retrieval based on Edge Responses, Shape and Texture Features using Datamining Techniques

Talluri. Sunil Kumar[1], T.V.Rajinikanth[2] and B. Eswara Reddy[3]

[1] VNR Vignana Jyothi Institute of Engineering and Technology, Hyderabad, Telangana, India

Received: 14 December 2015 Accepted: 1 January 2016 Published: 15 January 2016

Abstract

The present paper proposes a new technique that extracts significant structural, texture and local edge features from images. The local features are extracted by a steady local edge response that can sustain the presence of noise, illumination changes. The local edge response image is converted in to a ternary pattern image based on a local threshold. The structural features are derived by extracting shapes in the form of textons. The texture features are derived by constructing grey level co-occurrence matrix (GLCM) on the derived texton image. A new variant of K-means clustering scheme is proposed for clustering of images. The proposed method is compared with various methods of image retrieval based on data mining techniques. The experimental results on Wang dataset shows the efficacy of the proposed method over the other methods.

Index terms— local binary pattern, local directional pattern, textons, GLCM features.

1 I. Introduction

he volume of digital images produced in the world wide has increased dramatically over the past 10 decades and the World Wide Web plays a vital role in this upsurge. This has created the availability of huge digital image databases or libraries. The handling and accessing of these data base images by human annotations is impractical and it has led to the automatic search mechanisms and it has created a demand for content based image retrieval (CBIR) models. CBIR is defined as a process that searches and retrieves images from a large database. The retrieval operation is performed on the basis of derived image features such as color, texture and shape. A good literature survey was conducted on CBIR and is available in [1][2][3][4]. The color is one of the significant feature of the CBIR and one of the simple color based CBIR is the color histogram [5].The retrieval performance of this generally limited due to its low discrimination power mainly on immense data. To improve this various color descriptors are proposed in the literature using neural networks [6], DCT-domain vector quantization [7], supervised learning [8] and color edge co-occurrence histograms [9].

The natural images are visualized by their rich content of texture mosaic and color. The texture descriptors are based on grey scale variation and they can also integrate with color component of image retrieval (IR). It is very difficult to give unique definition to texture and it is one of the significant and salient features for CBIR. The texture based image retrieval is reported in the literature based on the characteristics of images in different orientations [10,11,12,13,14,15]. Extraction of texture features on wavelets [16], wavelet transform based texture features [16] and correlagrams [17] are also proposed for efficient IR. The performance of the correlograms [17] is further improved using genetic algorithms (GA) [18]. The integrated methods that combine the color histograms with texture features [19,20] and correlograms with rotated wavelets [21] attained a good IR rate. Recently, the research focuses on CBIR systems that is fetching the exact cluster of relevant images and reducing the elapsed time of the system. For this purpose, various data mining techniques have been developed to improve the performance of CBIR system. Clustering is one of the vital techniques of data mining for quick retrieval of information from the large data repositories. Clustering is an unsupervised process, thus the evolution of clustering algorithm is important due to the extraction of hidden patterns [22,23]. There are many applications in the real-world with clustering like credit card, mark analysis, web data categorization, image analysis, text mining, pattern recognition, market data analysis, weather report analysis [24].Data clustering explicitly divides the data into a set of k user specified number of groups by trying to minimize intra-cluster variance and maximize inter-cluster variance in an iterative manner [25,26]. Various methods are proposed in the literature to improve the performance of the data clusters [27,28,29] in various applications. K-means [30] is one of the popular and efficient clustering algorithms. Later various variations to k-means algorithm are proposed to improve the efficiency [31,32,33].

A content-based image retrieval method using adaptive classification and cluster-merging is proposed for image retrieval to find multiple clusters of a complex image query [34]. This method [34] achieves the same retrieval quality, under linear transformations, regardless of the shapes of clusters of a query. A cluster-based image retrieval system by unsupervised learning (CLUE), is proposed for improving user interaction with image retrieval systems by fully exploiting the similarity information [35]. The CLUE retrieves image clusters by applying a graph-theoretic clustering algorithm and it is dynamic in nature. The CLUE retrieves image clusters instead of a set of ordered images. The principle of unsupervised hierarchical clustering is also used in CBIR [36]. The modified fuzzy c-means (MFCM) clustering scheme introduced fuzzy weights and it reduced the time of clustering and also used for image retrieval [37, **??**6]. A content-based parallel image retrieval system to achieve high responding ability is proposed and it is based on cluster architectures [38]. It has several retrieval servers to supply the service of content-based image retrieval. Many researchers used k-means clustering with variations and achieved a good image retrieval rate [39,40,41,42]. K-means clustering technique is helpful to reduce the elapsed time of the system.

The rest of the paper organized as follows: The proposed method, local directional pattern (LDP),kmeans and query matching are given in Section 2. Experimental results and discussions are summarized in section 3. Based on above work, conclusions are made in section 4.

2 II. Proposed Method

The present paper initially converts the color image into grey level image using HSV quantization. The present paper derives integrated features that significantly holds edge, shape and texture features, for this initially edge responses are obtained then shape features in the form of textons are evaluated. Then GLCM features are obtained. Images are clustered based on the two point perimeter K-means (TPP-KM) clustering scheme. A similarity measure in the form of Euclidian distance is used to retrieve the top most similarity images.

3 a) Algorithm for feature extraction

The features are extracted based on the following steps

Step 1: The color image is converted in to grey level images using HSV color space.

Step 2: Conversion of edge response image in to ternary pattern image. This is derived based on two sub steps 2(a) and 2 (b).

Step 2 a): The local features in the form of edge responses in eight directions are obtained on the grey level image based on local direction pattern (LDP) coded image.

The formation process of LDP is explained below.

The LDP is an eight bit binary code that describes the relative edge value of a pixel in different directions [43]. The present paper evaluates edge responses in eight directions on a central pixel of a 3 x 3 neighborhood using Kirsch masks **??**68].Out of eight (m i /i=0, 1 ?.7) only the k-most significant edges are given a value 1 and the remaining are set to zero. The three greatest responses, i.e. k=3 are considered in the present paper. The reason for this is the occurrence of corner or edge indicates a huge edge response value in a particular direction. The LDP code generation on a 3x3 neighborhood is shown below in Figure **??** Image with noise

Step 2b): Conversion of LDP coded image in to ternary form, based on a threshold. This mechanism simplifies the extraction of textons that represent shape of the texture in the next step. This also makes the present process to be resistant to lighting effects, noise and neighborhood values are assigned one of the ternary values T i . (Equation **??**).

4 ???????? (??

??) = ? 2 ?? ?? ? (?? ?? + ??) 1 |?? ?? ? ?? ?? | < ?? 0 ?? ?? ? (?? ?? ? ??) (1)

The process of generation of this is illustrated in Figure 3 with l=3. The proposed edge responses generate a total of 0 to K*(P-1) codes and this is considered as the main disadvantage. Here k is the number of greatest edge responses considered and p is the number of neighboring pixels. This is not considered as the disadvantage in the present paper, since we are not deriving LDP coded image and we are only deriving ternary patterns out of the LDP coded image. Further it is more convenient to derive shape feature (in the next step) on local ternary patterns (0 or 1 or 2) derived from edge responses. Step 3: Derivation of local shape features in the form of textons on the ternary image. The method of deriving textons on ternary image is given in Figure 4. The basic unit of an image is pixels and its intensity and experiments based on this have not resulted any satisfactory results. In order to progress the performance the pattern and shape based methods are employed. A pattern and shape consists of group or set of neighboring pixels with similar intensity levels. One of such popular measure is "texton" proposed by Julesz [44]. Textons are defined as emergent patterns or blobs. These "textons" share a common property all over the image. The methods based on LBP and textons are very useful for texture analysis and classification [45,46,47] face recognition [48], age classification [49,50,51,52], image retrieval [15] etc. Variousarray grammar models are proposed in the literature to represent patterns and shapes [53,54].

Based on textons one can say whether texture is fine or coarse or in any other form. Textons can be derived on a 2x 2 or on a 3x3 or on any neighborhood window. The present paper utilized all texton patterns that forms only with two and four pixels on a 2×2 grid. This derives seven textons on a 2 x 2 grid. The derivation of texton image with the above 7 local shape features (textons) is shown below Figure 4. The present paper evaluated four Haralick features [55] for effective image retrieval and they are listed below. The features homogeneity, energy, contrast and correlation are evaluated with an angle of 0 o , 45 o , 90 o and 135 o and the average value of this are considered as texture feature. Homogeniety or Angular Second Moment (ASM):ASM= ? ? {P(i, j)} 2 G?1 j=0 G?1 i=0**(2)**

ASM is a measure of homogeneity of an image. A homogeneous scene will contain only a few grey levels, giving a GLCM with only a few but relatively high values of P (i, j). Thus, the sum of squares will be high.

Energy :Energy = ( ) 2 , , ? j i j i P (3) Contrast : Contrast=? n 2 G?1 n=0 ?? ? P(i, j) G j=1 G i=1 ?, |i ? j| = n**(4)**

This measure of contrast or local intensity variation will favor contributions from P (i, j) away from the diagonal, i.e. i ! = j.

Correlation :Correlation = ? ? {iXj }XP (i,j)??µ x Xµ y ? ? x X? y G?1 j=0 G?1 i=0 (5)

Correlation is a measure of grey level linear dependence between the pixels at the specified positions relative to each other.

5 b) Clustering method

One of the commonly used and simplest algorithm for clustering is the K-means algorithm. Kmeans is one of the fundamental algorithms of clustering and it employs the square error criterion. The numbers of partitions are to be defined in K-means initially. The cluster centers are randomly initialized for predefined number of clusters. If the initial number of clusters is not properly chosen then the output of algorithm may converge to false cluster locations and completely different clustering result **??**58, **??**9]. This measure is often called the squared-error distortion [60, The present paper outlined a new variation to the existing K-means algorithm to reduce the number of iterations and to increase the overall retrieval rate. This new variation of K-means scheme is denoted as two point perimeter -K-means (TPP-KM) clustering scheme. The present scheme selects two points instead of one point in K-means and also a perimeter is also evaluated and the similarity is evaluated by using Euclidean distance.

6 c) Query matching and performance measure

The present retrieval model selects 20 top images from the database images that are matching with query image. This is accomplished by measuring the distance between the query image and database images. The present paper used Euclidean distance as the distance measure and as given below???????? ?? (?? ?? , ?? ??) = ?? ?ð ??"ð ??" ?? (?? ??) ? ð ??"ð ??" ?? (?? ??)? 2 ??,?? =1 ? 1/2 (6)

The database image is used as the query image in our experiments. If the retrieved image belongs to the same category as that of query image we say that the system has suitably identified the predictable image otherwise the system fail to find the image. The performance of the present model is evaluated in terms of precision, recall rate and F-Measure as given in equation 7, 8 and 9.

7 ?????????????????? ?? =

???????????? ??ð ??"ð ??" ???????????????? ???????????? ?????????????????? (?? ????) ???????????? ??ð ??"ð ??" ?????????????????? ???????????? (?? ????) (7) ???????????? ?? = ???????????? ??ð ??"ð ??" ???????????????? ???????????? ?????????????????? (?? ????) ?????????? ???????????? ??ð ??"ð ??" ???????????????? ???????????? ???? ????? ???????????????? (?? ????) (8) The algorithms that improve precession may degrade recall and vice versa. The present paper also evaluates another parameter called F-measure that is based on both precession and recall.?? ? ?????????????? = 2 * (?????????????????? * ?????? ??????) (?????????????????? +????????????)**(9)**

8 III. Results and Discussion

In order to efficiently investigate the performance of the present retrieval model, we have considered the Wang database **??**64]. Wang is a subset of Corel stock photo database of 1000 images. These images are grouped into 10 classes, each class contains 100 images. Within this database, it is known whether any two images are of the same class. Classification of the images in the database into 10 classes makes the evaluation of the system easy. The hefty size of each class and the heterogeneous image class contents made Wang data base as one of the popular database for image retrieval. The present paper considered 7-classes of images and 100 images per each class. For a query image the relevant images are assumed to be the remaining 99 images of the same class. The images from all other classes are treated as irrelevant images. The retrieval performance of the proposed method is judged in terms of precession, recall and F-measure. The proposed clustering method derived integrated novel features from edge responses, shapes in the form of textons and statistical parameters in the form of texture features (GLCM features). The average retrieval performance of the proposed method is compared with CBIR methods using data mining techniques [65, 66, 67] and the proposed method with K-means clustering method. The proposed method outperformed all the other methods in terms of precession, recall and F-measure and this is shown in the Figure 5, 6 and Figure **??**. In the method [65] the features are extracted by GLCM features. In the existing method [67] fuzzy C-means clustering scheme is used with GLCM features and the method [66] used both color and statistical features with portioned clustering scheme. The advantage of the proposed method is the derivation of significant and powerful local features. Figure **??** shows seven examples of retrieval images, i.e. one image from each class, by the proposed method with 20-top most retrieved image. Where T n query image, I n image in database; The present paper proposed a CBIR method using a data mining algorithm. The proposed method used a simple clustering scheme and achieved high retrieval rate when compared with the other existing methods because the proposed method extracted powerful and significant local features derived from edge responses, shape and textural properties. As with many other clustering algorithms, a limitation with our algorithm is that it requires the number of clusters to be known in prior. The advantage of edge responses is it can sustain with non-monotonic illumination variation and random noise. The shape features derived from textons are rotationally invariant. The texture features in the form of GLCM features with the help of clustering scheme retrieved the images in an accurate manner. The proposed method is experimented with one of the popular and heterogeneous dataset "Wang" and the experimental results indicates the superiority of the present method over the other existing methods. Year 2016 ( ) F [1]

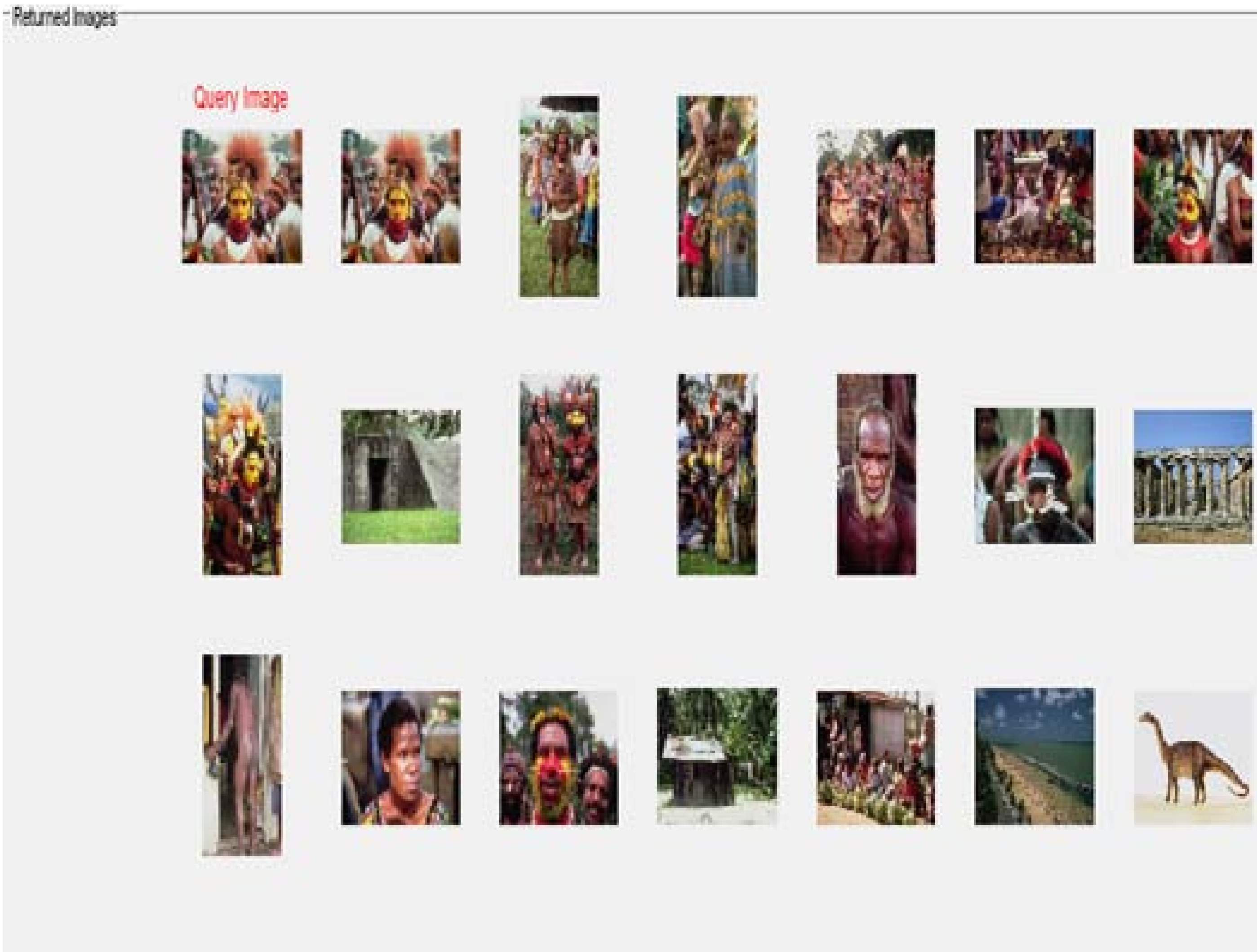
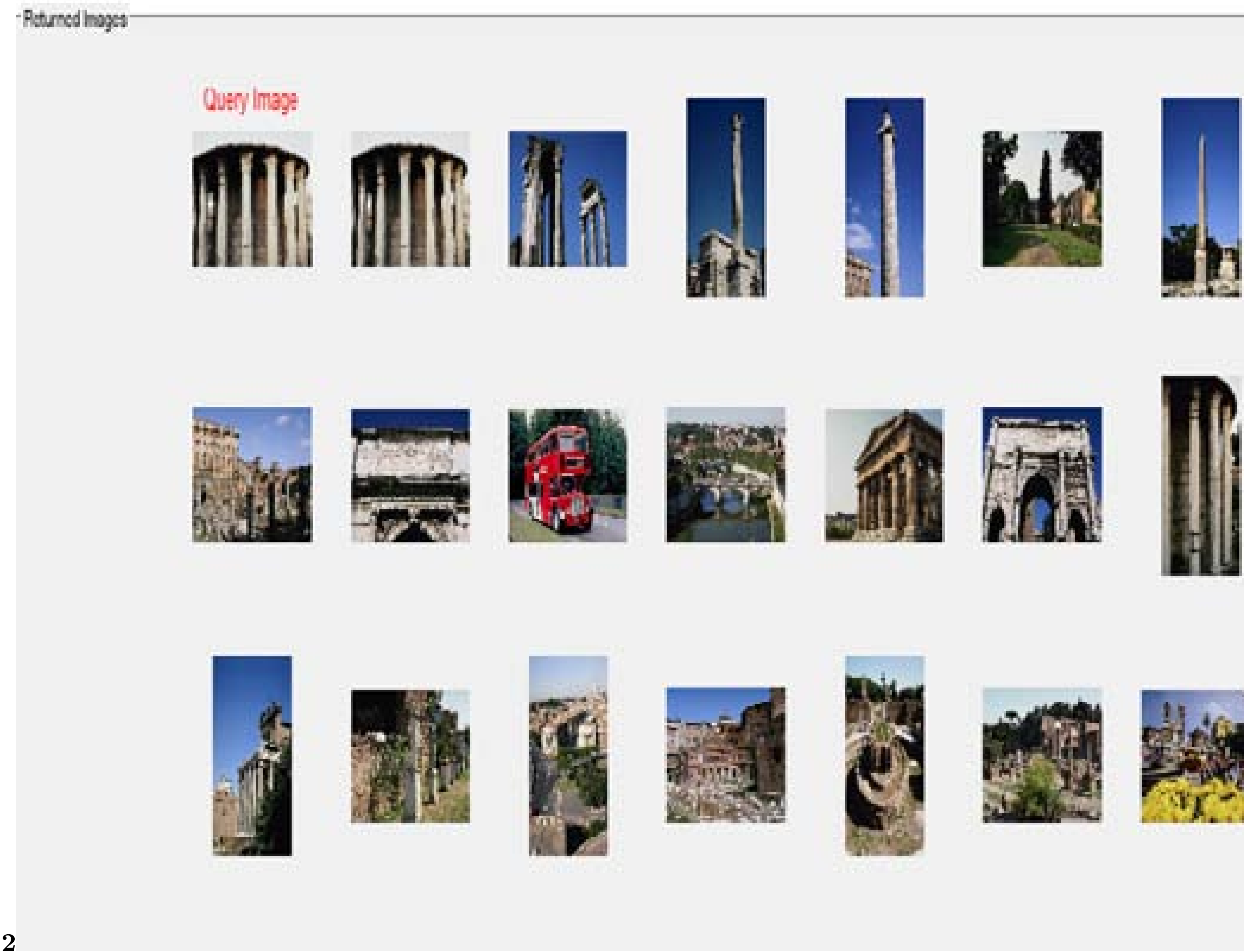


Figure 1:



2

Figure 2: Figure 2 :

3

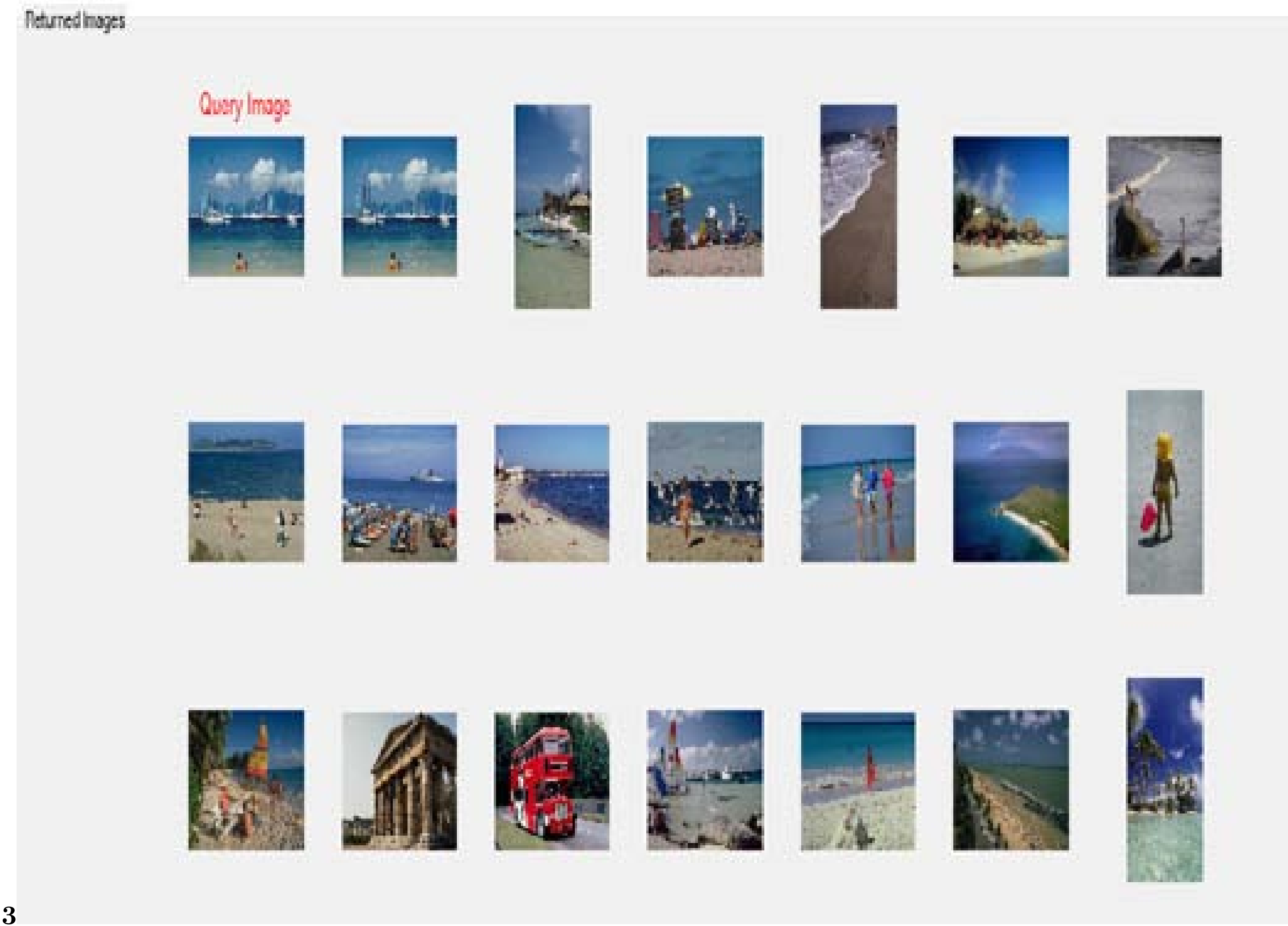
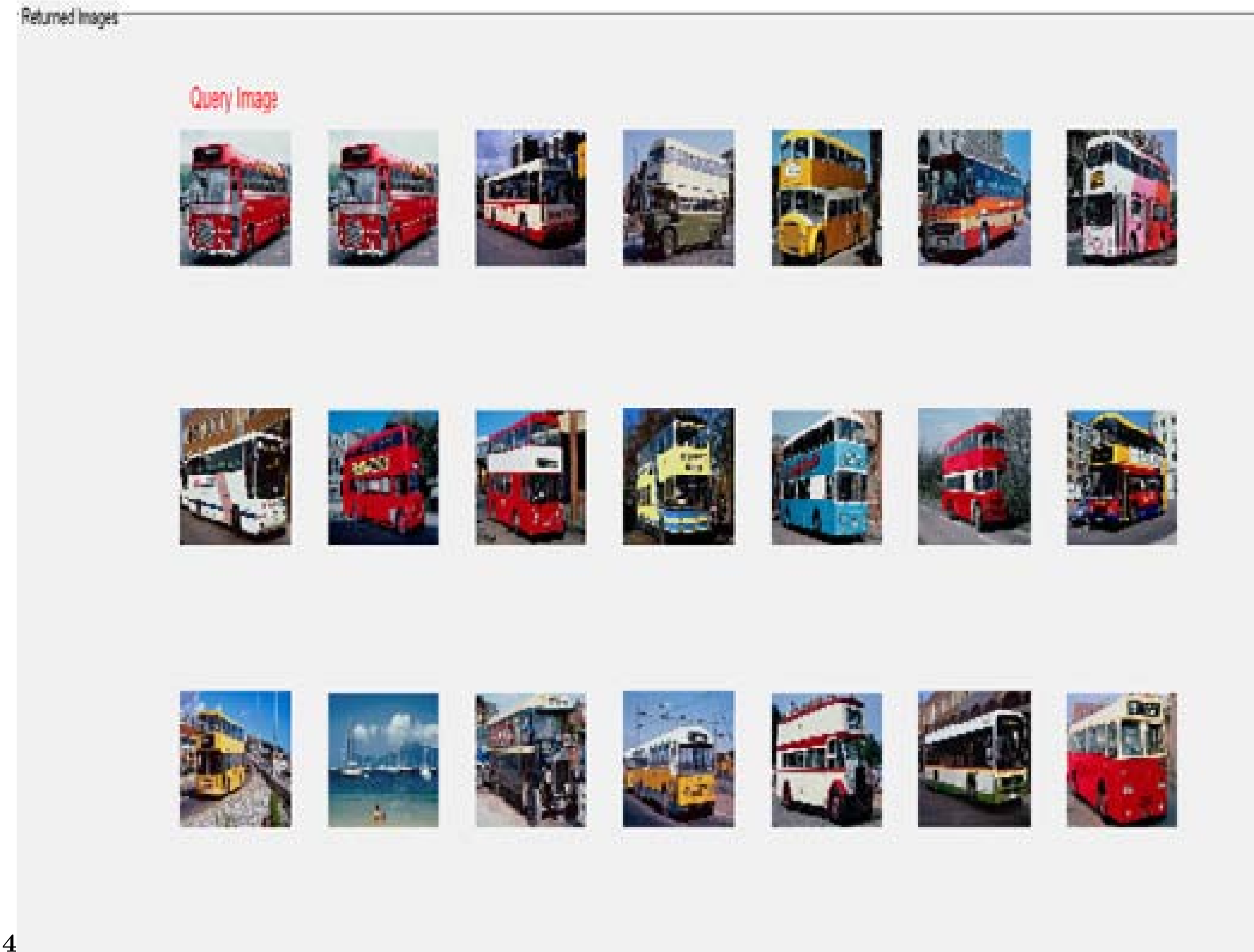


Figure 3: Figure 3 :



4

Figure 4: Figure 4 :

4

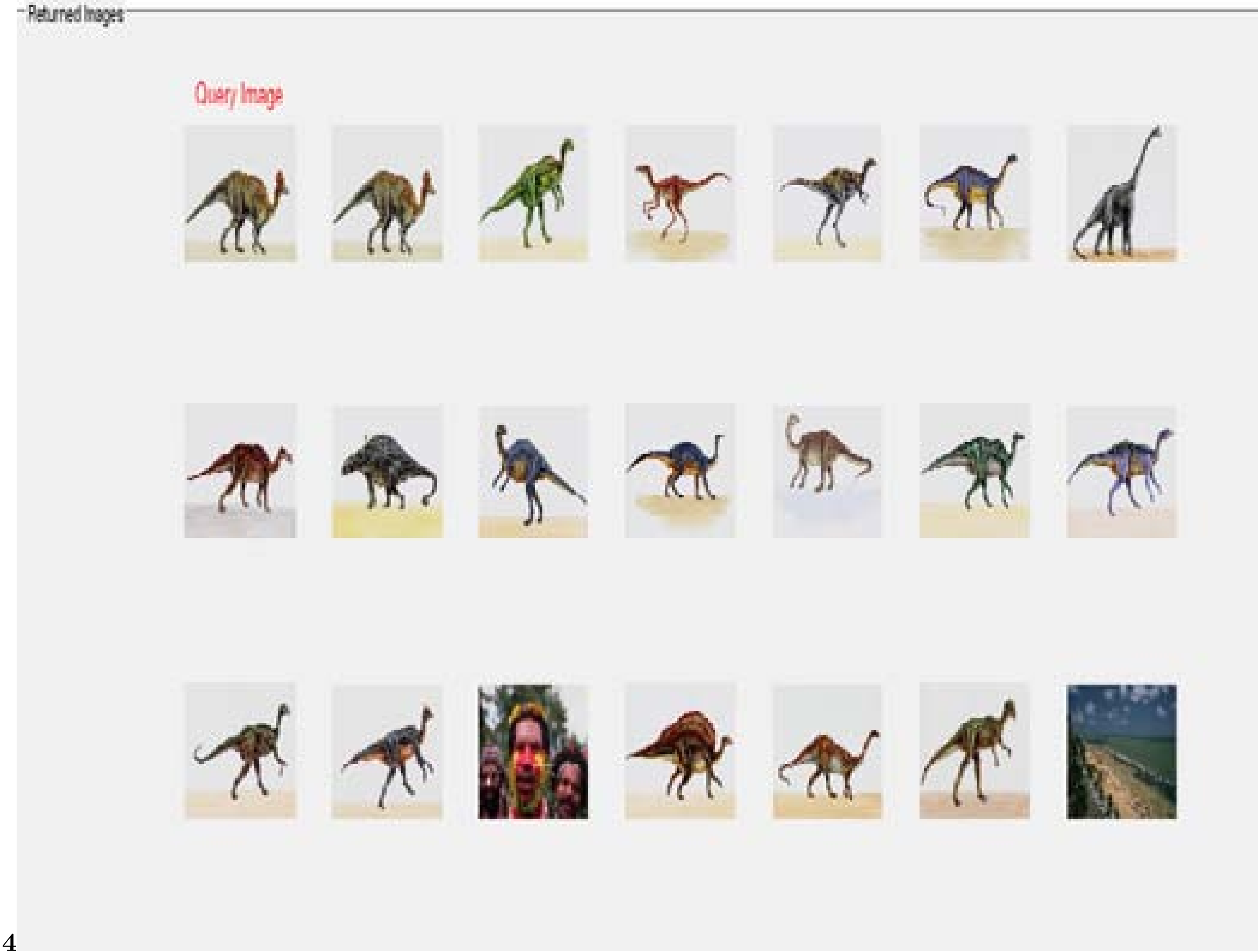


Figure 5: Step 4 :

5

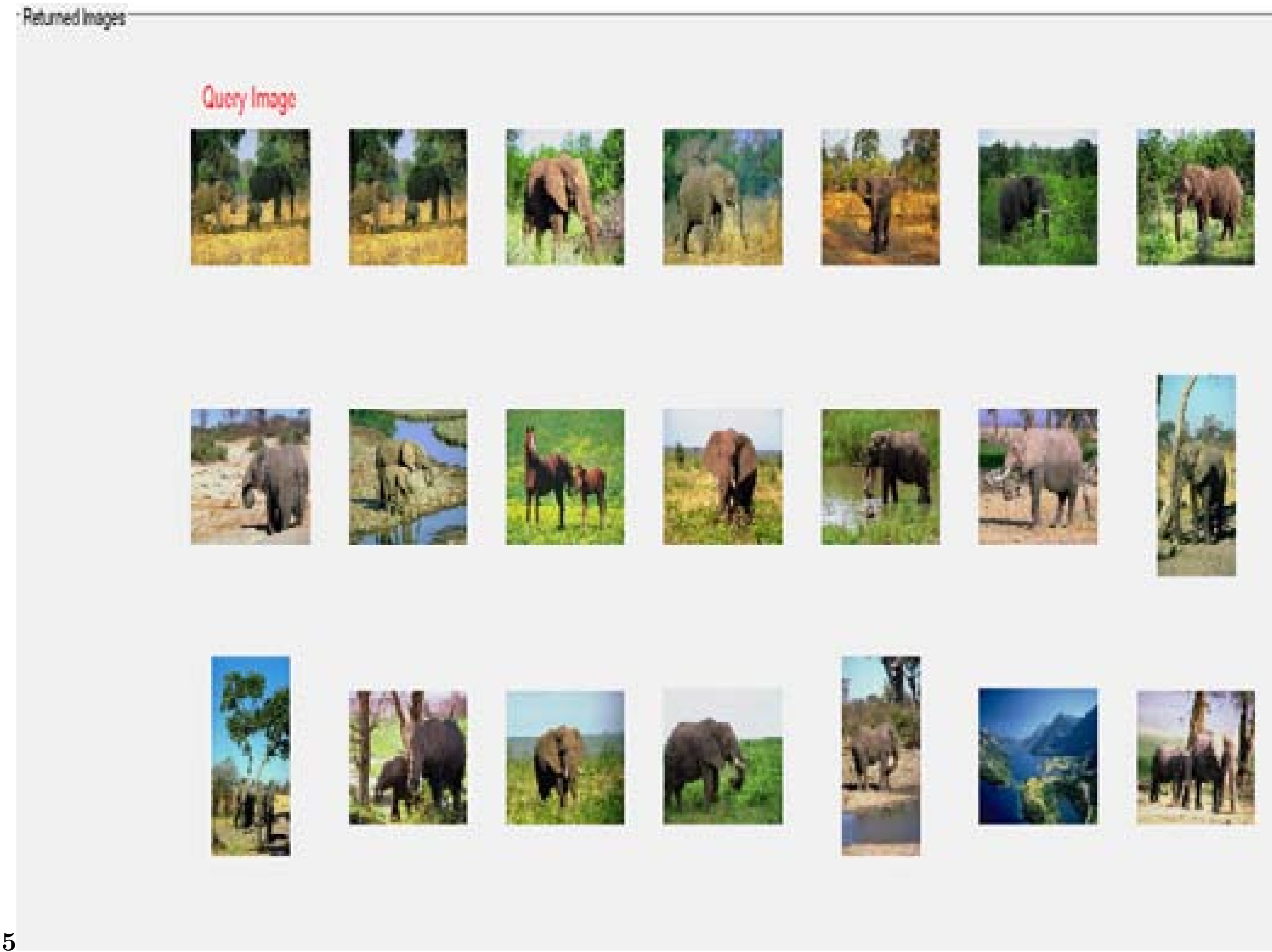


Figure 6: Figure 5 :F

76818

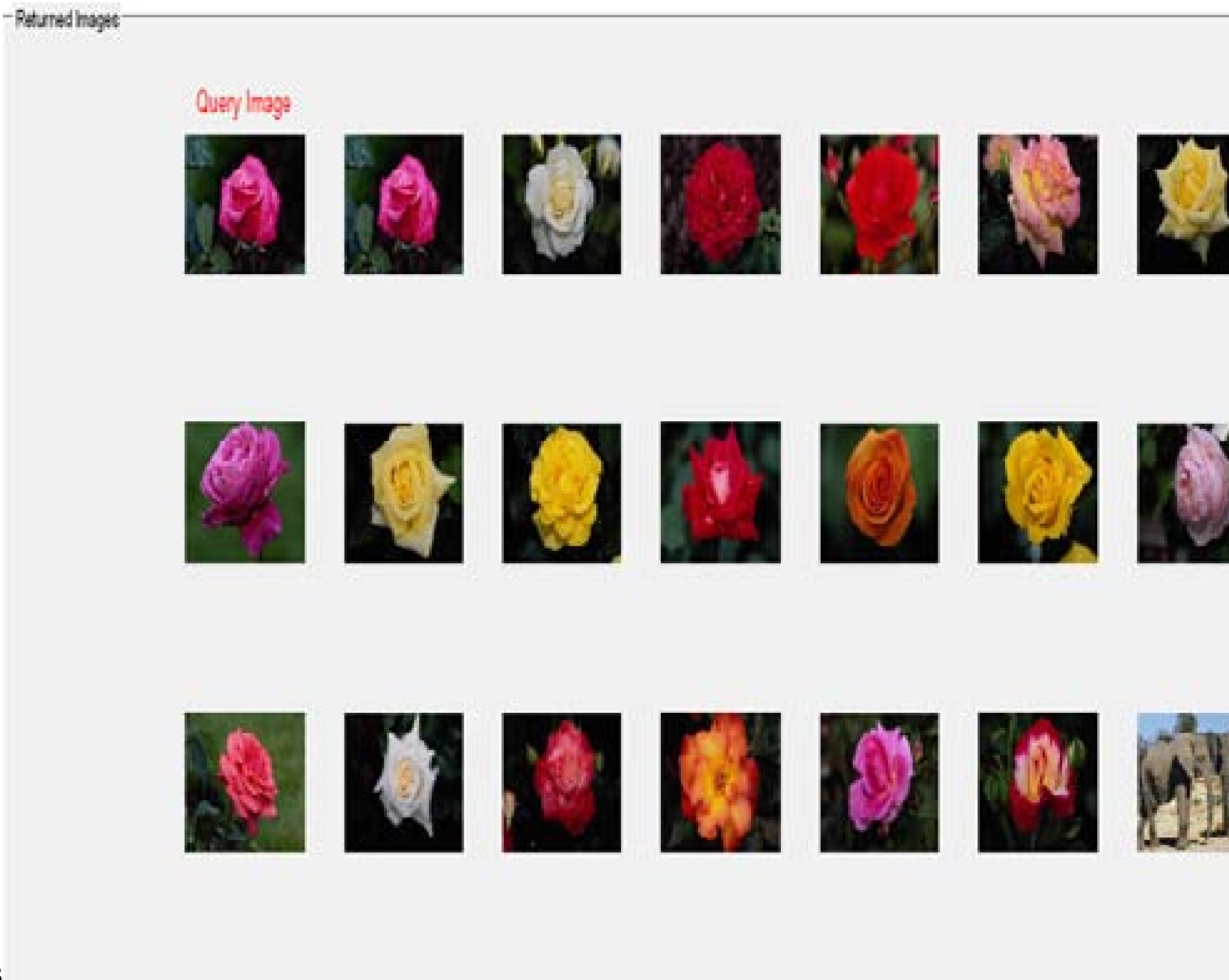


Figure 7: Figure 7 :Figure 6 :Figure 8 1 FFigure 8 F

[Prasad and V S N R V] , G Prasad , V S N R V .

[Krishna and Venkata] , V Krishna , Venkata .

[()] , 2016. 27 p. .

[Lei et al. ()] 'A CBIR method based on color-spatial feature, in: TENCON'. Z Lei , L Fuzong , Z Bo . *Proceedi-ngs of the IEEE Region 10 Conference*, (eedi-ngs of the IEEE Region 10 Conference) 1999. p. .

[Abduljawad and Amory ()] *A Content Based Image Retrieval Using K-means Algorithm*, A Abduljawad , Amory . 2012.

[Bing and Xin-Xin ()] 'A Content-based Parallel Image Retrieval System'. Zhou Bing , Yang Xin-Xin . *Int. Conf. On Computer Design And Appliations*, 2010.

[Subramnyam et al. ()] 'A correlogram algorithm for image indexing and retrieval using wavelet and rotated wavelet filters'. M Subramnyam , R P Maheshwari , R Balasubramanian . *Int. J. SignalImag. Syst.Eng* 2011. 4 (1) p. .

[Kumar et al. ()] 'A dynamic transform noise Resistant uniform Local Binary Pattern (DTNR-ULBP) for Age Classification'. P J S Kumar , V Krishna , V Vijaya , Kumar . *International Journal of Applied Engineering Research* 0973-4562. 2016. 11 (1) p. .

[Reddy et al.] 'A Method for Facial Recognition Based on Local Features'. K Reddy , V Krishna , V Vijaya , Kumar . *International Journal of Mathematics and Computation* 0974–570X.

[Moghaddam et al. ()] 'A new algorithm for image indexing and retrieval using wavelet correlograms'. H A Moghaddam , T Hajoie , A H Rouhi . *Int. Conf. Image Process*, (Tehran, Iran) 2003. 2 p. . N. Toosi Univ. of Technl.

[Ch et al. (2015)] 'A New Approach to Cluster Datasets without Prior Knowledge of Number of Clusters'. Ch , V Swetha Swapna , J V R Vijaya Kumar , Murthy . *JSIR* May 2015. 74 (05) .

[Raju et al. (2008)] 'A new method of texture classification using various wavelet transforms based on primitive patterns'. U S N Raju , K Chandra Sekharan , V V Krishna . *ICGST-Graphics, vision and image processing (ICGST-GVIP)*, July-2008. 8 p. .

[Sayal et al.] *A Novel Hybrid Clustering Algorithm: Integrated Partitional and Hierarchical clustering algorithm for categorical data"-International journal of computer science and Emerging Technologies*, Rishi Sayal , Gvsr Dr , Dr V Vijaya Prasad , Kumar . (IJCSET))

[Lin et al. ()] 'A smart contentbased image retrieval system based on color and texture feature'. C H Lin , R T Chen , Y K Chan . *Image Vis. Comput* 2009. 27 (6) p. .

[Coggins and Jain ()] 'A spatial filtering approach to texture analysis'. J M Coggins , A K Jain . *Pattern Recogni-non Letters* 1985. (3) p. .

[Gorti S Murty et al. ()] 'Age classification based on simple LBP transitions'. V Gorti S Murty , A Kumar , Obulesu . *International journal of computer science and engineering (IJCSE)* OCT-2013. 5 (10) p. .

[Vijaya Kumar et al. ()] 'Age classification of facial images using third order neighbourhood Local Binary Pattern'. P J S Vijaya Kumar , Kumar , S V V S R Pullela , Kumar . *International Journal of Applied Engine-ering Research* 0973-4562. 2015. 10 p. . (Number)

[Jain and dubes ()] *Algorithms for Clustering Data*, A Jain , R &dubes . 1988. 1988. Englewood Cliffs, NJ: Prentice-Hall.

[Vijaya Kumar et al. (2013)] 'An effective age classification using topological features based on compressed and reduced grey level model of the facial skin'. Jangala Vijaya Kumar , V V Sasikiran , Hari Chandana . *International journal of image, graphics and signal processing (IJIGSP)*, Nov-2013. 6 p. .

[Pengyu and Jiakebin ()] 'An Effective and Fast Retrieval Algorithm for Content-based Image Retrieval'. Liu Pengyu , Lvzhuoyi Jiakebin . *Congress on Image and Signal Processing*, 2008.

[Alsabti et al. (1998)] 'An Efficient K-means Clustering Algorithm'. K Alsabti , S Ranka , V Singh . *Proc. First Workshop High Performance Data Mining*, (First Workshop High Performance Data Mining) 1998 March.

[Jarrah et al. ()] 'Automatic Content-Based Image Retrieval Using Hierarchi-cal Clustering Algorithms'. K Jarrah , Sri Krishnan , Ling Gum . *Int. Joint Conf. on Neural Networks*, July 16-21, 2006.

[Karâa ()] *Biomedical Image Analysis and Mining Techniques for Improved Health Outcomes*, W B A Karâa . 2015. (IGI Global)

[Chen et al. ()] 'CLUE: Cluster-Based Retrieval of Images by Unsupervised Learning'. Y Chen , J Z Wang , R Krovetz . *IEEE Trans. Image Processing* AUGUST 2005. 14 (8) .

[Kumar and Vijaya (2011)] 'Clustering Approaches Based On Initial Seed Points'. V Kumar , Vijaya . *International Journal on Computer Science and Engineering* Dec 2011. 3 (12) p. . (Automatic)

[Wu et al. ()] 'Color and texture feature for content based image retrieval'. J Wu , Z Wei , Y Chang . *Int. J. Digit. Content Technol. Appl* 2010. 4 (3) .

[Birgale et al. ()] 'Color and texture features for content based image retrieval'. L Birgale , M Kokare , D Doye . *Int. Conf. Comput. Grafics. Image Visual*, (Wash., USA) 2006. p. .

[Subramanyam et al. ()] 'Color and texture features for image indexing and retrieval'. M Subramanyam , A B Gonde , R P Maheshwari . *IEEE Int. Adv. Comput. Conf. Patial., Ind* 2009.

[Luo and Crandail ()] 'Color object detection using spatial-color joint probability function'. J Luo , D Crandail . *IEEE transitions on Image Processing*, 2006. 15 p. .

[Kekre and Thepade ()] 'Color traits transfer to grayscale images'. H B Kekre , S D Thepade . *IEEE Int. Conference on Emerging Trends in Engineering and Technology* 2008. ICETET.

[Cinque et al. ()] 'Colour-based image retrieval using spatial-chromatic histogram'. L Cinque , G Ciocca , S Levialdi , A Pellicano , R Schettini . *Image Vis. Comput* 2001. 19 p. .

[Nagthane (2013)] 'Content Based Image Retrieval Using K-means clustering technique'. Deepika Nagthane . *Int. Jour. of CAIT* June-July 2013. 3.

[Yue et al. ()] 'Content-based image retrieval using color and texture fused features'. J Yue , Z Li , L Liu , Z Fu . *Math. Comput. Modelling* 2011. 54 p. .

[Pentland et al. ()] 'Content-based manipulation of image databases'. R W Pentland , S Picard , Photobook Sclaroff . *Int. J. Comput. Vis* 1996. 18 p. .

[Jain et al. ()] 'Data clustering: A review'. A Jain , M Murty , P Flynn . *ACM Comput. Surv* 1999. 31 (3) p. .

[Kumar et al. ()] 'Dual Transition Uniform LBP Matrix for Efficient Image Retrieval'. V Kumar , A Srinivasa Rao , Yk Sundara Krishna . *I.J. Image, Graphics and Signal Processing* 2015. 8 p. .

[V Vijaya Kumar et al. (2009)] 'Employing long linear patterns for texture classification relying on wavelets'. U S N V Vijaya Kumar , Chandra Raju , V V Sekaran , Krishna . *ICGST-Graphics, vision and image processing (ICGST-GVIP)*, Jan-2009. 8 p. .

[Murthy et al. (2014)] 'Employing simple connected pattern array grammar for generation and recognition of connected patterns on an image neighborhood'. Vishnu G Murthy , V Kumar , B V Reddy . *ICGST-Graphics vision and image processing*, Aug-2014. 14 p. . (ICGST-GVIP))

[Saadatmand and Moghaddam ()] 'Enhanced wavelet correlogram methods for image indexing and retrieval'. M T Saadatmand , H A Moghaddam . *IEEE Int.Conf. Image Procc*, (Iran) 2005. p. . N. Toosi Univ. of Technol. Tehran

[Obulesu et al. (2015)] 'Facial image retrieval based on local and regional features'. A Obulesu , J S Kiran , Kumar . *IEEE-2015 International Conference on Applied and Theoretical Computing and Communication Technology (iCATccT)*, Oct. 2015. p. .

[Pun and Wong ()] 'Fast and robust, color feature extraction for content-based image retrieval'. C M Pun , C F Wong . *Int. J. Adv. Comput. Technol* 2011. 3 (6) .

[Liu et al. ()] 'Fast Query Point Movement Techniques for Large CBIR Systems'. D Liu , K A Hua , K Vu , N Yu . *IEEE Trans. on Knowledge and Data Engg* MAY 2009. 21 (5) .

[Vadivel et al. ()] 'Human color perception in the HSV space and its application in histogram generation for image Retrieval'. A Vadivel , S Sural , A K Majumdar . *Proc. SPIE, Color Imaging X: Processing, Hardcopy, and Applications*, (SPIE, Color Imaging X: essing, Hardcopy, and Applications) 2005. p. .

[Saxena et al. ()] 'Image Retrieval using Clustering Based Algorithm'. Akash Saxena , Sandeep Saxena , Akanksha Saxena . *International Journal of Latest Trends in Engineering and Technology* 2012.

[Jeong et al. (2004)] 'Image retrieval using color histograms generated by Gauss mixture vector quantization'. S Jeong , C S Won , R M Gray . *Computer Vision Image Understanding*, iss-1-3, june-2004. 94 p. .

[Ch et al.] 'Improving Efficiency of K-Means Algorithm for Large Datasets'. Ch , V Swapna , J V R Kumar , Murthy . *International Journal of Rough Sets and Data Analysis* 3 (2) . (IJRSDA))

[Sayal and Kumar (2012)] 'Innovative Modified K-Mode Clustering algorithm'. Rishi Sayal , Dr V Vijaya Kumar . *Interna-tional journal of Engineering Research and Applications (IJERA)* July 2012. 2 p. .

[Karaa et al. ()] 'MEDLINE Text Mining: An Enhancement Genetic Algorithm Based Approach for Document Clustering'. W B A Karaa , A S Ashour , D B Sassi , P Roy , N Kausar , N &dey . *Applications of Intelligent Optimization in Biology and Medicine*, 2016. Springer International Publishing. p. .

[Vijaya Kumar et al. ()] 'New method for classification of age groups based on texture shape features'. P Vijaya Kumar , B Eswara Chandra Sekhar Reddy , Reddy . *International journal imaging and robotics* 0974-0637. 2015. 15 (1) .

[Murthy et al. (2014)] 'Overwriting grammar model to represent 2D image patterns'. Vishnu G Murthy , V Vijaya , Kumar . *ICGST-Graphics vision and image processing*, Dec-2014. 14 p. . (ICGST-GVIP)

[Kim and Chung (June 9-12)] ‘Qcluster: Relevance Feedback Using Adaptive Clustering for Content-Based Image Retrieval’. Deok-Hwan Kim , Chin-Wan Chung . *SIGMOD 2003*, June 9-12.

[Berrani ()] *Recherche approximative de plus prochesvoisinsaveccontr?oleprobabiliste de la pr´ecision; application ‘a la recherchedimages*, S A Berrani . 2004. (par le contenu, PHD thesis, 210 pages)

[Jabid et al. ()] ‘Robust facial expression recognition based on local directional pattern’. T Jabid , M H Kabir , O Chae . *ETRJ journal* 2010. 32 (5) p. .

[Juntao and Xiaolong ()] *School of computer science and technology china university of mining and Technology*, Wang Juntao , Su Xiaolong . 2011. p. . (An improved K-Means clustering algorithm)

[Mcqueen ()] ‘Some methods for classification and analysis of multivariate observations’. J Mcqueen . *Proc. of 5th Berkeley Symposium on Mathema-tical Statistics and Probability*, (of 5th Berkeley Symposium on Mathematical Statistics and Probability) 1967. p. .

[Julesz ()] ‘Textons, the elements of texture perception, and their interactions’. B Julesz . *Nature* 1981. 290 (5802) p. .

[Haralick et al. ()] ‘Textural features for image classification’. R M Haralick , K Shanmugan , I Dinstein . *IEEE Trans. Sysr., Man., Cybern* 1973. 3 (6) p. .

[Reddy et al. (2014)] ‘Texture classification based on binary cross diagonal shape descriptor texture matrix (BCDSDTM)”, ICGST-Graphics vision and image processing’. P. Kiran Kumar Reddy , V Kumar , B Eswar Reddy . *ICGST-GVIP)*, Aug-2014. 14 p. .

[Manjunathi and Ma ()] ‘Texture features for browsing and retrieval of image data’. B S Manjunathi , W Y Ma . *IEEE Trans. Pattern Anal. Mach. Intell* 1996. 8 (8) p. .

[Kokare et al. ()] ‘Texture image retrieval using rotated wavelet filters’. M Kokare , P Biswas , B Chatterji . *J. Pattern Recognition. Lett* 2007. 28 p. .