Australian Journal of Basic and Applied Sciences, 9(11) May 2015, Pages: 322-328

ISSN:1991-8178

Australian Journal of Basic and Applied Sciences

Journal home page: www.ajbasweb.com

CBIR Based on Non-Parametric Statistical Tests of Hypothesis

[1]S. Selvaraj and [2]K. Seetharaman

[1]*Research Scholar, Dept. of Computer Science, Manonmaniam Sundaranar University, Tirunelveli, India*
[2]*Department of Computer Science and Engineering, Annamalai University, Annamalainagar-608002, Tamilnadu, India*

ARTICLE INFO

Article history:
Received 6 March 2015
Accepted 25 April 2015
Published 9 May 2015

Keywords:
Color, Database, Image, Query, Shape

ABSTRACT

The field of image processing is addressed significantly by the role of CBIR. Peculiar query is the main feature on which the image retrieval of content based problems is dependent. Relevant information is required for the submission of sketches or drawing and similar type of features. Many algorithms are used for the extraction of features which are related to similar nature. The process can be optimized by the use of feedback from the retrieval step. Analysis of color and shape can be done by the visual contents of image. Here neural network, Relevance feedback techniques based on image retrieval are discussed.

© 2015 AENSI Publisher All rights reserved.

To Cite This Article: S. Selvaraj, K. Seetharaman, CBIR Based on Non-Parametric Statistical Tests of Hypothesis, ***Aust. J. Basic & Appl. Sci.,*** *9(11): 322-328, 2015*

INTRODUCTION

In recent years, a number of researchers have turned their attention to the content-based image retrieval (CBIR) system. In CBIR system, the researchers concentrate on developing low-level global visual features, namely color properties, shape, texture, and spatial relationship etc., which are used as query for the retrieval process. The method proposed in classifies or segments the entire image into various regions according to the objects or structures present in the image, and the region-to-region comparison is made to measure the similarity between two images. In a region-based system, the user has to provide one or more regions from the query image to start a query session. Automatic and precise extraction of image objects is still beyond the ability of the retrieval system available with the computer vision. Therefore, the above system tends to partition one object into several regions, but none of them is representative of the semantic object.

Content Based Image Retrieval:

Content Based Image Retrieval (CBIR), is a new research for many computer science groups who attempt to discover the models for similarity of digital images. Content Based Image retrieval method uses visual content of images for retrieving the most similar images from the large database. In this method visual contents from images in the database are extracted. Now whenever user gives an image to a system as input, it extracts the visual content from that image and compares the visual content (features) with the visual content of the images in database and retrieves the most similar images. Thus, CBIR uses the visual content of image such as color, shape, texture for represent and index the images.

Feature Extraction:

When input image (data) to an algorithm is too large to be processed and it is assumed to be disgracefully redundant, then the input image is transformed into a reduced set of features which is known as feature vector. Thus transforming an input data into set of features is called feature extraction. It is done by visual content descriptor. The descriptor could be two types either global or local. A global descriptor uses the visual feature of the whole image whereas a local descriptor use visual features of objects or regions to describe image content. The descriptor extracts the low level visual feature such as color, shape, texture and makes the feature vector.

Color Extraction:

Color is the most expansively used visual content for image retrieval. Before choosing effective color descriptors for feature extraction first color space must be determined. Usually colors are defined in three dimensional color spaces which could be RGB (Red, Green, and Blue), HSV (Hue, Saturation and Value) and Opponent color space. RGB is widely used color space for image display and display is made using primary color (red, green, blue) or mixing of these colors. HSV color space is mostly used in computer graphics and most sensitive

Corresponding Author: S. Selvaraj, Research Scholar, Dept. of Computer Science, Manonmaniam Sundaranar University, Tirunelveli, India

way of describing color. Here first component Hue is invariant to change in camera direction and illumination so it is most suitable for object retrieval. The Opponent color space use opponent color axes (R-G, 2B-R-G, R+G+B) and has advantage of differentiating brightness information on third axis and first two axis is invariant to change in shadow and illumination intensity. Some most widely use color descriptors are:

Color Histogram:

It is used for effective representation of color content of an image if color pattern is unique compared with the rest of data. It is easy to compute for both global and local distributor of color. Though it is a good method for color extraction, it does not take the spatial information of pixels into consideration so very different images can have same color distribution.

Color Moment:

It has been successfully used in many retrieval systems especially when the image contains just object. The first order (mean), second orders (variance), third order (skewness) color moment have been proved to be efficient and effective in representing color distribution of images. Here third order moment improves the overall retrieval performance but it is very sensitive the changes in scene and sometimes decreases the performance.

Color Coherence Vector:

Color coherence vector is same as color histogram method but here color histogram also take the spatial information of pixel. Here each histogram is divided into two types i.e. coherent, if it belongs to large uniform color region or incoherent, if it does not. It provides better result than color histogram especially for most uniform color or texture region.

Color Correlegram:

The color correlegram is projected to characterize not only the color distributions of pixels but also gives the information about the spatial correlation of pairs of colors. It gives best performance than color coherence vector and color histogram but has large computational expensive due to high dimensity.

Shape Extraction:

Shape feature of object or region is be extracted for retrieving the images from the database. Number of features of object shape is computed for every object identified.Two main types of shape features most commonly extracted are global features (such as aspect ratio, circularity and moment invariants) and local features (such as sets of consecutive boundary segments).The methods of feature extraction are divided in two major categories either boundary based (rectilinear shape, polygonal approximation and Fourier based shape descriptors) and region based (statistical moments.

A good shape representation feature should be invariant to translation, rotation and scaling. Some of the widely used shape descriptors for shape feature extraction are as follows:

Polygonal Approximation:

Polygonal approximation can be put to ignore the minor variations along the edge, and instead capture the overall shape information. In this method there are two ways to extract feature from shape, merging and splitting. Merging methods add successive pixels to a line segment if each new pixel that is added doesn't cause the segment to deviate too much from a straight line .Splitting methods work by first drawing a line from one point on the boundary to another then compute the perpendicular distance from each point along the boundary segment to the line. If this exceeds some threshold, break the line at the point of greatest distance. Repeat the process recursively for each of the two new lines until no longer need to break any more. It is simple method for contour representation and description.

Moment Invariant:

Moment invariant is also called as geometric moment. There are total seven moments which is used for shape feature extracted. The most important advantage of using this moment invariant is that they are invariant to rotation, scaling and translation. Also the moments are simple in compute. There are some disadvantages of this method like higher order moments are very sensitive to noise and this moments also suffer from information redundancy because its basis is not orthogonal.

Texture Extraction:

Texture is that inherent property of all surfaces that describes visual patterns and contains significant information about the structural arrangement of the surface and its relationship to the surrounding environment. Various texture representations have been investigated in computer vision and pattern recognition. The texture representation method can be classified in four major groups: (i) Structural (ii) Statistical (iii) Model based methods (iv) Signal Processing based methods.

1. Structural Methods: Structural methods represent the texture by well defined primitives and spatial arrangement of these primitives. So for feature extraction this primitive may be extracted. Once the primitives have been extracted, the analysis is completed by computing statistics of the primitives (e.g. intensity, area, elongation, and orientation). These methods are very effective when textures are in regular pattern but mostly natural images do not have regular patterns of texture so it is not good for

those images. Morphological and various clustering methods are example of these.

2. Statistical Methods: Statistical methods examine the spatial distribution of gray values by computing local features at each point in the image, and deriving a set of statistics from the local features. Depending on the number of pixels that defining the local feature statistical methods can be further classified into first-order (one pixel), second-order (two pixels) and higher-order (three or more pixels) statistics. The basic difference between those methods are : first-order statistics estimate properties (e.g. average and variance) of individual pixel values, ignoring the spatial interaction between image pixels, where second- and higher-order statistics estimate properties of two or more pixel values occurring at specific locations relative to each other. Grey Level Co occurances Metrix (GLCM), Local Binary Pattern are widely used statistical methods.

3. Model based Methods: Model based texture analysis method use the fractal and stochastic models and make effort to interpret an image texture by use of respectively, generative image model and stochastic model. The parameters of the model are estimated and then used for image analysis. The disadvantage of this method is high computational complexity that arising in the estimation of stochastic model parameters. The model based method has been useful for modeling some natural textures however it lacks orientation selectivity and is not suitable for describing local image structures. Autoregressive model, Markov Random field, Gauss-Markov random field are some model based methods those are use for texture feature extraction.

4. Signal Processing Based Methods: Signal processing based method represent an image in a space whose coordinate system has an interpretation that is closely related to the characteristics of a texture (such as frequency or size). Both frequency and spatial domain approaches are used for filtering the image and then relevant information is captured. Various transform like Fourier, Wevelet, Gabor etc. are example of this method. Signal processing method gives better result than any type of methods for feature extraction but computational time of these methods may be large.

Evaluation Parameters of Image Retrieval:

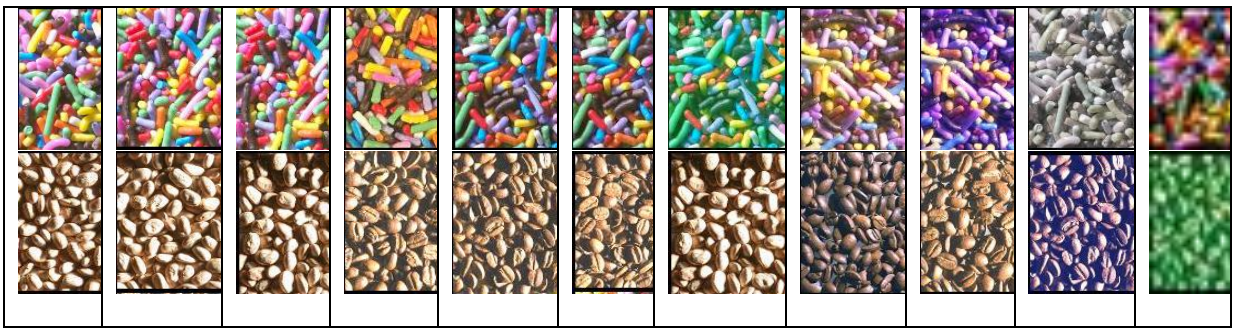
In this paper, we use the standard measures such as precision and recall to evaluate the results. These parameters are defined as below:

$$\text{Recall} = \frac{-\text{Number of images retrieved and relevant}}{\text{Total number of relevent images in the database}}$$

$$\text{precision} = \frac{-\text{Number of images retrieved and relevant}}{\text{Total number of retrieved images}}$$

Image Database Design and Experimental Results:

In order to implement the proposed method, 477 color images of size 512×512 pixels have been collected from online image database resources, i.e. 113 texture images from SIPI database, 102 images from CuReT image database and 100 images from KTH-TIPS image database. The remaining 58 images with size 128×128 are photographed with our digital camera; 43 images with size 128×128 have been downloaded from internet [30]. The textured images collected from SIPI, CuReT and KTH-TIPS image databases are divided into 12 non-overlapping sub-images of size 128×128. To examine the proposed system is invariant for rotation and scaling; the images are rotated by 900 , 1800 and 2700 , and scaled. To validate the proposed system, based on statistical non-parametric tests. Due to space constraints, for sample, some of the images considered for the experiment are presented in Figures 1 and 2. The experiment is conducted at various levels of significance for the input query image given in column 1 of Figure 1. The images in columns 2, 3, 4, 5 of Figure 1 are retrieved at level of significance, 0.001; images in columns 6, 7 are retrieved at 0.05 level of significance; at 0.15 level of significance, the system retrieves the images in columns 8, 9, 10 and 11.



Australian Journal of Basic and Applied Sciences, 9(11) May 2015, Pages: 322-328

Table 1: Performance measure of the proposed method with other existing methods

Database	Statistical Distributed Approach		Orthogonal Polynomial Method		Gabor Wavelet Transform Method		Contourlet Transform Method		Proposed Method	
	Recall	Precision	Recall	Precision	Recall	Precision	Recall	Precision	Recall	Precision
SIPI	0.835	0.784	0.812	0.825	0.825	0.661	0.825	0.601	0.838	0.789
CUReT	0.811	0.816	0.808	0.822	0.824	0.663	0.824	0.613	0.818	0.824
1) KTH-TIPS	0.814	0.814	0.811	0.824	0.822	0.668	0.823	0.612	0.820	0.826
VisTex	0.810	0.810	0.782	0.681	0.795	0.670	0.805	0.610	0.812	0.814
Structure Images	0.843	0.815	-	-	-	-	0.826	0.621	0.851	0.824

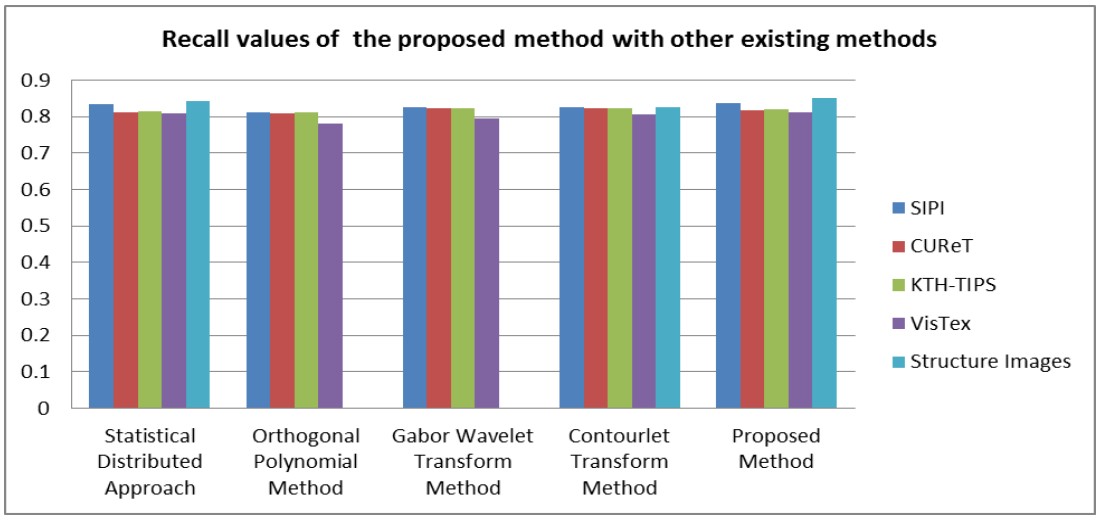


Fig. 1: Recall values of the proposed method with other existing methods

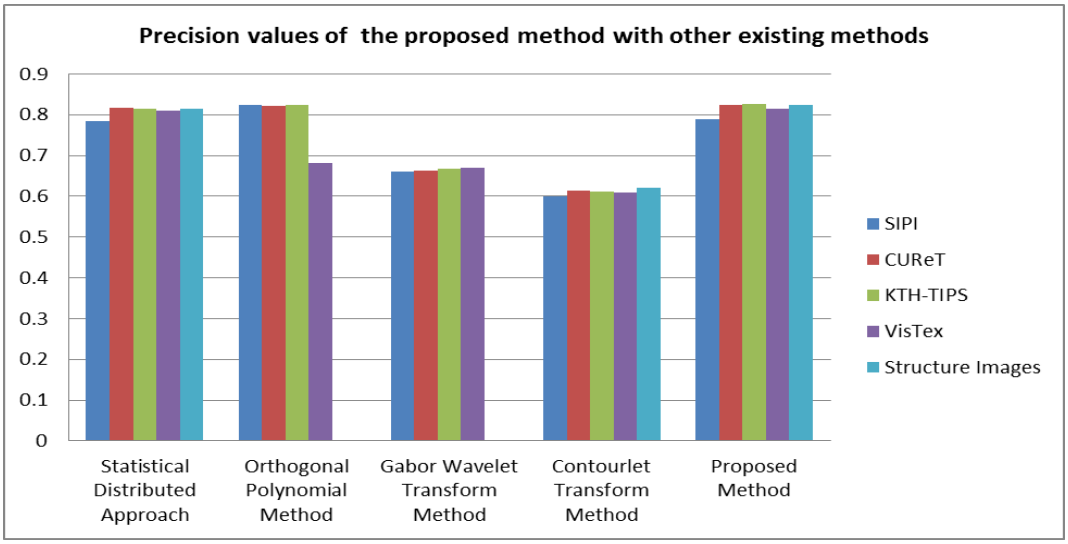


Fig. 2: Precision values of the proposed method with other existing methods

A comparative study is performed with the existing methods such as Orthogonal polynomial [19], Gabor wavelet transform [20] and the Contourlet transform method [27] methods and Statistical distributional approach [28], and the obtained results are presented in Table 1. The results reveal that the proposed method outperforms the existing methods. It is observed from the results that there is no significant difference between the proposed method and the statistical distributional approach. Though both parametric and non-parametric tests yield almost same results; there are some difficulties to employ parametric tests. Since some type of images may not be distributed to Gaussian, at that situation the parametric tests cannot be applied. Thus, the necessity arises to use appropriate non-parametric tests instead of parametric tests.

Conclusion:

Block-wise sampling technique proposed in does not yield good results for the rotated and scaled color images, because the corresponding blocks of query (actual) and target (transformed) images do not match spatially, while the target image is rotated in any direction or scaled. Hence, the technique proposed in fails to match and retrieve the right images in the existing technique. The proposed system avoids this problem, because it uses the global distributional differences of both query and target images; in the case of structured images, these features are extracted from the shapes in both query and target images, and those are compared shape-wise, it compares the number of shapes with different pixels between the images. The orthogonal polynomial based methods retrieve only textured images with gray scale, and the Gabor features based method retrieves only the textured images in both color and gray-scale. The proposed system retrieves both textured and structured color images of different image databases downloaded from the Internet, and it is robust for scaled and rotated images. Most of the other methods retrieve a set of similar images, from which the user has to select the required images. But the our proposed system facilitates the user to retrieve the required image only by fixing the level of significance at a desired level.

Here in this work, a unified system for both structured and textured color image retrieval is used, based on statistical non-parametric tests of hypothesis. The proposed system is invariant for rotation and scaling, since the query image is treated as either a sample or population of the target image. First, the test for equality of variation between the query and target images is performed; the query and target images pass the test, viz. the two images are same or similar, then the test for equality of mean vectors is performed, i.e. testing the spectrum of energy on the same images. The proposed system provides hundred percent accuracy and precision, even if either the target or query image is rotated or scaled.

REFERENCES

Huang, J., S.R. Kunar, M. Mitra, W.J. Zhu and R. Zabih, 1997. Image indexing using color correlogram, in: Proc. IEEE Comp. Soc. Conf. Comp. Vis. and Pattern Recognition, 1: 762-768.

Stricker, M. and M. Orengo, 1995. Similarity of color images, in: Storage and Retrieval for Image and Video Databases, Proc. SPIE 2420, 1: 381-392.

Pentland, A., R. Picard and S. Sclaroff, 1996. Photobook: Content-based manipulation of image databases, International Journal of Computer Vision., 18(3): 233-254.

Chiou-Shaan Fuh, Shun-Wen Cho and Kai Essig, 2000. Hierarchical color image region segmentation for content-based image retrieval system, IEEE Transactions on Image Processing, 9(1): 156-162.

Jing, F., M. Li, H.J. Zhang and B. Zhang, 2004. An efficient and effective region-based image retrieval framework, IEEE Transactions on Image Processing, 13(5): 699-709.

Jun-Wei Hsieh and W. Eric L. Grimson, 2003. Spatial template extraction for image retrieval by region matching, IEEE Transactions on Image Processing, 12(11): 1404-1415.

Belongie, S., C. Carson, H. Greenspan and J. Malik, 2002. Recognition of images in large databases using color and texture, IEEE Transactions on Pattern Analysis and Machine Intelligence, 24(8): 1026-1038.

Jing, F., B. Zhang, F.Z. Lin, W.Y. Ma and H.J. Zhang, 2001. A novel region-based image retrieval method using relevance feedback, in: Proc. 3rd ACM Int. Workshop on Multimedia Information Retrieval (MIR).

Deng, Y. and B.S. Manjunath, 1999. "An efficient low-dimensional color indexing scheme for regionbased image retrieval, in: Proc. IEEE Int. Conf. ASSP", 6: 3017-3020.

Ing-Sheen Hsieh and Huo-Chin Fan, 2001. "Multiple classifiers for color flag and trademark image retrieval", IEEE Transactions on Image Processing, 10(6): 938-950.

Smith, J.R. and C.S. Li, 1999. "Image classification and querying using composite region templates, Journal of Computer Vision and Image Understanding", 75(12): 165-174.

Du, Y.P., 2001. "Scalable integrated region-based image retrieval using IRM and statistical clustering", in: Proc. ACM and IEEE Joint Conference on Digital Libraries, VA, 2001, pp: 268-277.

Rahimi, M., M.H. Alizadeh, R. Rajabi and N. Mehrshad, 2001. The Comparison of Innovative Image Processing and Goniometer Methods in Q Angle Measurement, World Applied Sciences Journal, 18(2): 226-232.

Rui, 1998. Yong. Relevance feedback a power tool for interactive content-based image retrieval, Circuits and Systems for Video Technology, IEEETransactions, pp: 644-655.

MacArthur, S.D., C.E. Brodley, A.C. Kak and L.S. Broderick, 2002. Interactive content-based image retrieval using relevance feedback, Computer Vision and Image Understanding, 88(2): 55-75.

Arevalillo-Herráez, Miguel, and Francesc J. Ferri, 2013. An improved distance-based relevance feedback strategy for image retrieval, Image and Vision Computing, 31(10): 704-713.

da Silva, André Tavares, Jefersson Alex dos Santos, Alexandre Xavier Falcao, Ricardo da S. Torres, and Léo Pini Magalhães, 2012. Incorporating multiple distance spaces in optimum-path forest classification to improve feedback-based learning,

Computer Vision and Image Understanding, 116 (4): 510-523.

Piras, Luca and Giorgio Giacinto, 2012. Synthetic pattern generation for imbalanced learning in image retrieval, Pattern Recognition Letters, 33(16): 2198-2205.

Metternich, Michael J, and Marcel Worring, 2013. Track based relevance feedback for tracing persons in surveillance videos, Computer Vision and Image Understanding, 117(3): 229-237.

Saneifar, Hassan, Stéphane Bonniol, Pascal Poncelet and Mathieu Roche, 2014. Enhancing passage retrieval in log files by query expansion based on explicit and pseudo relevance feedback, Computers in Industry, 1-15.

Wang, Xiang-Yang, Yong-Wei Li, Hong-Ying Yang, and Jing-Wei Chen, 2014. An image retrieval scheme with relevance feedback using feature reconstruction and SVM reclassification, Neurocomputing, (127): 214- 230.

Shyu, Mei-Ling, Shu-Ching Chen, Min Chen, and Chengcui Zhang, 2004. A unified framework for image database clustering and content-based retrieval, Proceedings. 2nd ACM international workshop. on Multimedia databases, pp: 19-27.

Quack, Till, Ullrich Mönich, Lars Thiele and B.S. Manjunath, 2004. Cortina: a system for large-scale, content-based web image retrieval, Proceedings.12th annual ACM international .conference on Multimedia, 508-511.

Lin, Wei-Hao, Rong Jin, and Alexander Hauptmann, 2003. Web image retrieval re-ranking with relevance model , Proceedings. IEEE/WIC International Conference .on Web Intelligence, pp: 242-248.

Wang, Xin-Jing, et al, 2004. Multi-model similarity propagation and its application for web image retrieval, Proceedings .12th annual ACM international conference. On Multimedia, pp: 944-951.

Schaefer, Gerald and Michal Stich, 2004. UCID: an uncompressed color image database, Proc. SPIE 5307 .on Storage and Retrieval Methods and Applications for Multimedia, pp: 472-480.

Yu, Hui, Mingjing Li, Hong-Jiang Zhang, and JufuFeng, 2002. Color texture moments for content-based image retrieval In Image Processing, Proceedings. International Conference on IEEE, (3): 929-932.

Kekre, H.B, and Sudeep D. Thepade, 2008. Boosting Block Truncation Coding with Kekre's LUV Color Space for Image Retrieval, International Journal of Electrical, Computer & Systems Engineering, 2(3).

Gagaudakis, George and Paul L. Rosin, 2002. Incorporating shape into histograms for CBIR,Pattern Recognition, 35(1): 81-91.

Zhang, Dengsheng, and GuojunLu, 2001. Content-Based Shape Retrieval Using Different Shape Descriptors: A Comparative Study, ICME, pp: 1-4.

Mussarat Yasmin, Muhammad Sharif, Sajjad Mohsin, 2013. Image Retrieval Techniques Using Shapes of Object: A Survey, Sci.Int (Lahore), 25(4): 723-729.

Yasmin, Mussarat, Sajjad Mohsin, Isma Irum, and Muhammad Sharif, 2013. Content based image retrieval by shape, color and relevance feedback, Life Science Journal, 10(4s): 593-598.

Prasad, B.G., K.K. Biswas and S.K. Gupta, 2004. Region-based image retrieval using integrated color, shape, and location index, Computer vision and image understanding, 94(1): 193-233.

Singh, Chandan, 2011. Improving image retrieval using combined features of Hough transform and Zernike moments, Optics and Lasers in Engineering, 49(12): 1384-1396.

Cheng, Heng-Da, X.H. Jiang, Ying Sun and Jingli Wang, 2001. Color image segmentation advances and prospects, Pattern recognition, 34(12): 2259-2281.

Qin, Chanchan, Guoping Zhang, Yicong Zhou, Wenbing Tao, and Zhiguo Cao, 2013. Integration of the saliency-based seed extraction and random walks for image segmentation, Neurocomputing, (129): 378-391.

Zhang, Jun and Lei Ye, 2010. Series feature aggregation for content-based image retrieval, Computers & electrical engineering, 36(4): 691-701.

Seetharaman, K and S. Sathiamoorthy, 2014. Color image retrieval using statistical model and radial basis function neural network, Egyptian Informatics Journal, 15(1): 59-68.

Sánchez-Cruz, Hermilo and Ernesto Bribiesca, 2009. Polygonal approximation of contour shapes using corner detectors, Journal of applied research and technology, 7(3): 275-290.

Tao, Dacheng, Xiaoou Tang, Xuelong Li, and Yong Rui, 2006. Direct kernel biased discriminant analysis: a new content-based image retrieval relevance feedback algorithm, Multimedia IEEE Transactions, 8(4): 716-727.

Yasmin, Mussarat, Muhammad Sharif and Sajjad Mohsin, 2013. Neural Networks in Medical Imaging Applications: A Survey, World Applied Sciences Journal, 22(1).

Noda, Kuniaki, Hiroaki Arie, Yuki Suga and Tetsuya Ogata, 2014. Multimodal integration learning of robot behavior using deep neural networks, Robotics and Autonomous Systems, 62(6): 721-736.

Kurtz, Camille, Christopher F. Beaulieu, Sandy Napel and Daniel L. Rubin, 2014. A hierarchical knowledge-based approach for retrieving similar medical images described with semantic annotations, Journal of biomedical informatics, pp: 1-18.

Gao, Chao, Dongguo Zhou, and YongcaiGuo, 2013. Automatic iterative algorithm for image

segmentation using a modified pulse-coupled neural network, Neurocomputing, (119): 332-338.

Son, Le Hoang, Nguyen Duy Linh and Hoang Viet Long, 2013. A lossless DEM compression for fast retrieval method using fuzzy clustering and MANFIS neural network, Engineering Applications of Artificial Intelligence, pp: 33-42.

Humberto Sossn, ElizabethGuevara, 2013. Efficient training for dendrite morphological neural networks, Neurocomputing, pp: 132-142.

Sudipta.Mukhopadhyay, 2013. A new content-based image retrieval technique using fuzzy class membership,NeuroComputing, 34(6): 646– 654.

Abrahams, Alan S. Eloise Coupey, Eva X. Zhong, Reza Barkhi and Pete S. Manasantivongs, 2013. Audience targeting by B-to-B advertisement classification: A neural network approach, Expert Systems with Applications, 40(8): 2777- 2791.

Milanova, Mariofanna, Roumen Kountchev, Stuart Rubin, Vladimir Todorov, and Roumiana Kountcheva, 2009. Content Based Image Retrieval Using Adaptive Inverse Pyramid Representation, ,In (First Ed) ,Human Interface and the Management of Information and Interaction, pp: 304-314.

Yasmin, Mussarat, Sajjad Mohsin and Muhammad Sharif, 2013. Intelligent Image Retrieval Techniques A Survey, Journal of Applied Research and Technology, 12(1): 87-103.

Seo, Kwang-Kyu, 2007. An application of one-class support vector machines in content-based image retrieval, Expert Systems with Applications, 33(2): 491-498.

Su, Zhong, Hongjiang Zhang, Stan Li, and Shaoping Ma, 2003. Relevance feedback in content-based image retrieval Bayesian framework, feature subspaces and progressive learning, Image Processing IEEE Transactions, 12(8): 924- 937.

Lew, Michael S., Nicu Sebe, Chabane Djeraba and Ramesh Jain, 2006. Content-based multimedia information retrieval State of the art and challenges, ACM Transactions on Multimedia Computing, Communications, and Applications (TOMCCAP), 2(1): 1-19.

Seetharaman, K., M. Jeyakarthic, 2014. Statistical distributional approach for scale and rotation invariant color image retrieval using multivariate parametric tests and orthogonality condition, Journal of Visual Communication Image Representation, 25(5): 727-739.