International Journal of Engineering & Technology, 7 (2.19) (2018) 1-6

International Journal of Engineering & Technology

Website: www.sciencepubco.com/index.php/IJET

Research paper

Feature Extraction in JPEG domain along with SVM for Content Based Image Retrieval

D.Mansoor Hussain [1]*, Dr. D. Surendran [2], A. Benazir Begum [3]

[1] Assistant Professor,Sri Krishna college of Engineering and Technology, Coimbatore
2 Professor,Sri Krishna college of Engineering and Technology, Coimbatore
3 Assistant Professor,Akshaya college of Engineering and Technology, Coimbatore
**Email: mansoor.slm@gmail.com*

Abstract

Content Based Image Retrieval (CBIR) applies computer vision methods for image retreival purposes from the databases. It is majorly based on the user query, which is in visual form rather than the traditional text form. CBIR is applied in different fields extending from surveillance to remote sensing, E-purchase, medical image processing, security systems to historical research and many others. JPEG, a very commonly used method of lossy compression is used to reduce the size of the image before being stored or transmitted. Almost every digital camera in the market are storing the captured images in jpeg format. The storage industry has seen many major transformations in the past decades while the retrieval technologies are still developing. Though there are some breakthroughs happened in text retrieval, the same is not true for the image and other multimedia retrieval. Specifically image retreival has witnessed many algorithms in the spatial or the raw domain but since majority of the images are stored in the JPEG format, it takes time to decode the compressed image before extracting features and retrieving. Hence, in this research work, we focus on extracting the features from the compressed domain itself and then utilize support vector machines (SVM) for improving the retrieval results. Our proof of concept shows us that the features extracted in compressed domain helps retrieve the images 43% faster than the same set of images in the spatial domain and the accuracy is improved to 93.4% through SVM based feedback mechanism.

Keywords: *JPEG (Joint Photographic Experts Group), DCT (Discrete Cosine Transform); CH (Color Histogram); SVM (Support Vector Machine);term frequency–inverse document frequency, Precision and Recall*

1. Introduction

Content based image retrieval research exist as early as 1990's and is still continuing for a major breakthrough. The semantic complexity leads to different descriptions and hence there is a need for an efficient algorithm to bridge the semantic gap. Several algorithms were tried in the past and were able to produce significant results but most of them exist in the pixel space or in the raw domain. Indexing and Searching are the two phases involved in CBIR systems. Indexing takes care of extracting the features from the image while searching algorithms are used to match the user query with the images in the database for retrieval.
Space and time limitations are pushing the need for the images to be stored in compressed formats as soon as they are captured.Image indexing in this compressed domain brings out many advantages as compared to the pixel domain feature extraction principles. This includes, reduction in overall computation due to the limited size, quicker retreival results due to the time saved in decoding process and finally better features due to presence of only needed information in the compressed images.

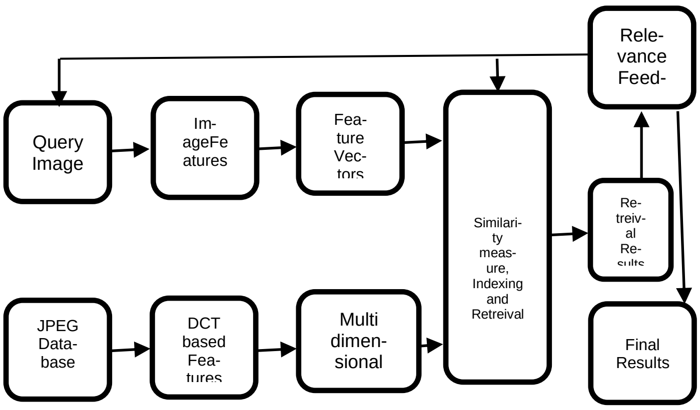

Fig 1.1: Content Based Image Retreival System with relevance feedback mechanism

A typical CBIR system with feature extraction and similarity matching is represented in Fig 1.1, along with the relevance feedback mechanism for improvising the retreival results. The CBIR system user will provide his test input in the form of a picture or a drawing. The system will then extract the features from this query image and match it with all the features in the database to retrieve back the matching ones.

In this paper, we introduce a novel image indexing method in the DCT domain and then add it up with the support vector machine based feedback mechanism, which is a new try in compressed domain.
Relevance feedback is a procedure normally used to improve the performance of a CBIR system. It could be either explicit or implicit. In case of explicit feedback, the user gets to know about the importance of his opinion and it normally carries a grading system with it. Implicit feedback on the other hand infers from the user behaviour and adjusts the weightages accordingly internally for retrieving the results every time. There are different supervised and semi-supervised machine learning algorithms available for this purpose including decision trees, neural networks, Bayesian methods, generative models, support vector machines and genetic algorithms to name a few. In this work, we have used support vector machines as it avoids over-fitting, contains kernel trick and is the best for optimization problems. In addition, the “tf-idf” method helps us in assigning weighting factors during relevance feedback mechanism. All this put together, makes our work novel and improves the retrieval accuracy in shorter time when compared with the traditional methods in the literature.

2. Related works

CBIR is a hot topic in digital image processing techniques and is discussed in detail for the past two decades. There are wide varieties of research publications in this field but not many are converted in to projects or products for commercial usage. The two major bottlenecks in this research are the semantic gap between the user query and the system understanding along with the retrieval time. If these two issues are addressed, then we will have more success in making an effective retreival system.
Baisakhi Sur Phadikar along with Amit Phadikar and Goutam Kumar Maity [1] have proposed content-based image retreival in DCT domain with the help of genetic algorithms.FazalMalikand Baharum Baharudin [2] used the quantized histogram statistical texture features extracted in compressed domain using the substantial energy of the DC component and the first three AC coefficients of the DCT blocks. Corel image database is used for their experimentation and they find their results to be robust when compared to other similar retreival mechanisms.
David Edmundson and Gerald Schaefer [3] compared the various retrieval methods in detail and proposed two other methods to extract the information from the header.Optimized Huffman tables and quantization table provides them with the sufficient information required for the data retreival with needed accuracy.
Color is a primitive feature in CBIR system that cannot be avoided and majority of the paper talks about this for image retreival in one form or another. Zhe-Ming Lu, Su-Zhi Li and Hans Burkhardt have used color, spatial and texture features on the DCT domain [4] and reduced the computational complexity of the indexing and retreival algorithms.
Relevance feedback helps in improving the CBIR performance in terms of precision and recall parameters. Lokesh Setia, Julia Ick and Hans Burkhardt [5] have discussed about support vector machine based relevance feedback in image retreival using invariant feature histograms. They also compare the efficiency of one class and two class SVM in CBIR systems using these histograms.However, this is performed on the pixel domain features extracted and is different from what we are proposing in this paper.
Raghupathi Gali, M. L. Dewal and R. S. Anand [8] have used a real coded chromosome genetic algorithm as fitness function to optimize the feature weights. Their experimentation results shows that the optimal weights of features computed by the algorithm improvises the retrieval results significantly.
One of the numerical statistic “tf-idf” helps in placing the weightage of a particular word’s importance in a document for text retrieval [18]. We extend the similar metric for image retreival as well by giving weightage to a particular feature based on the feedback from the end user and adjust this accordingly on every iteration.Yu Suzuki, Masahiro Mitsukawa and Kyoji Kawagoe [19] have used tf-idf approach to find the importance degree of features and by using their method, the CBIR system can find results matching the user query to the closest possible.
There are several other algorithms proposed in the literature and analysed frequently by different researchers [21, 22] but most of them lack in either retreival accuracy or the time taken to retrieve the results. We have bridged this gap in this proposed work and detailed in the coming sections.
An easy way to comply with the paper formatting requirements is to use this document as a template and simply type your text into it.

3. JPEG standard and proposed work

JPEG is not a file format but a compression standard. It is based on the Discrete Cosine Transformation (DCT).Every image is split in to 8*8 blocks and each of these pixel groups are separately encoded with its own discrete cosine transform. It can be further exactly replicated by 64 cosine waves. The first one is called the DC component representing the general intensity of that particular block while the rest 63 AC coefficients follow the same. One of the interesting factor is that the low frequency components have a much bigger impact than the high frequency ones in the DCT transformed image.For this reason, these high frequency components is removed through the process called as quantization and only the needed ones are preserved back. It is to be noted that the added sum of the product of these coefficients with the cosine waves will produce back the original image or the block.Huffman coding is the final step in JPEG compression, which gets finally stored along with the header information.
The JPEG decompression follows the exact reverse process as shown in Fig 1.2 and in this work; we concentrate majorly on DCT high frequency coefficients along with the JPEG header for building a robust CBIR system. The DCT equation in this whole compression process is given by

$$G_{u,v} = \frac{1}{4}\alpha(u)\alpha(v)\sum_{x=0}^{7}\sum_{y=0}^{7} g_{x,y}\cos\left[\frac{(2x+1)u\pi}{16}\right]\cos\left[\frac{(2y+1)v\pi}{16}\right]$$

Here ‘u’ represents the horizontal spatial frequency; v symbolizes the vertical spatial frequency. g(x,y) matches to pixel value at co-ordinates (x,y) and G(u,v) characterizes the DCT coefficients at co-ordinates (u,v).

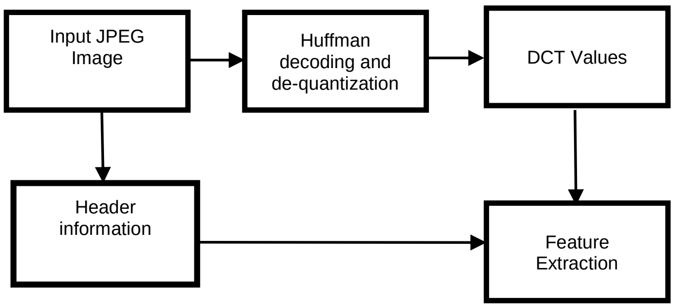

Fig 1.2: Feature Extraction from JPEG compressed image

By means of using the DCT coefficients directly, we avoid computationally intensive IDCT (Inverse Discrete Cosine Transformation) process and extract the features easily from the Luma region
of the YCbCr image rather than the typical RGB image in pixel space. We form the feature vector space involving the following components for retrieval purposes:

1. DC terms from Luma plane that hold the mean values of each pixel block in the image
2. Color information from the DC coefficients of the CbCr planes from each block

3. Texture information through the local binary pattern on DC coefficients of the Y channel
4. Adapted Huffman and quantization tables present in the JPEG header
5. Tf-idf based weighting factor to these features and then adjusting it with the help of SVM based relevance feedback mechanism.

Once the feature vectors are extracted, a norm or a function is needed to assign a size to each vector in a vector space. There are different norms available including absolute value norm, Euclidean norm, P-norm and maximum norm. We have proposed to use the Taxicab or the Manhattan norm in this research work as it shows better precision values as compared to its counterparts and provide us the advantage of absolute value distance, which is more robust as opposed to squared error distance and clusterd towards the performance[28].
Through these different feature vectors along with the feedback mechanism, our proposed system outweighs the other methods discussed in the literature in terms of retreival accuracy as well time. The following sections details the feature extraction in detail along with the SVM based relevance feedback mechanism[29] for effective content-based image retrieval system.

4. Feature Extraction in the DCT domain

The Discrte Cosine Transformation by itself gives a good amount of features for image retrieval by removing the redundant information and keeping only the needed ones. We try to simplify it still and take out the most valuable information that helps in building our CBIR system. While most methods decompress the image, extract features in the pixel domain and then use it for similarity matching, we extract the features directly in the compressed domain thereby saving both time and improving the retrieval results.

4.1. Energy Information from DCT blocks

The DC coefficient is an important feature in DCT domain and it represents the average energy of an image. We collect this information across all blocks and store in independently as our first feature vector.

4.2. Color Feature from DCT

Color is a widely used CBIR feature for representing the image. Color histograms including fuzzy histograms are common in CBIR systems. Color moments is a low dimension feature and does not have huge computational complexity as compared to the color histograms. We concentrate on color moments hence in the DCT blocks. While the Y plane follow the luminous efficiency function of the human visual system, the Cb and Cr planes provide the required color information of the image. Hence, we extract color on this chroma portion of the JPEG image.
Low frequency here represents the smooth color change while the high frequency corresponds to drastic changes. While mean, standard deviation and skewness are generally used in extracting the color moments, we use hue and saturation as it is more consistent with the human perception in terms of image description. It is given by:

$$\text{Hue} = 2 + (Cb - Cr) / (\max - \min) \qquad \dots (1)$$

This value is further multiplied by 60 to get it converted in to degrees on the color circle. There is no saturation if the max and the min values are the same. Otherwise, it is calculated as:

$$\text{Saturation} = (\max - \min) / (\max + \min) \qquad \dots (2)$$

Though we could add more features, we limit to these as far as color is concerned because different objects or contents can have the same color and can lead to false positives. In addition, fewer items will lead to faster similarity matching.

4.3. Texture Feature from DCT

We categorizethe top left quadrant of each DCT block in to multiple regions and get the texture information from the horizontal, vertical and diagonal regions in it. Each sub block is treatedindividually as represented in Fig 1.3 below:

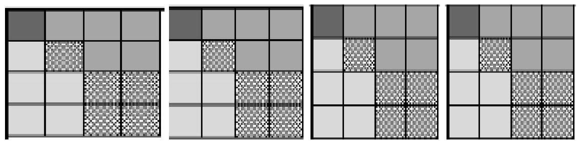

Fig 1.3: Texture Extraction from DCT blocks

The three directional texture vectors are extracted from each block and handled for further usage.It is given by:

$$H_{ij} = (C10, C20, C30, C21, C31) \qquad \dots (1)$$

$$V_{ij} = (C01, C02, C03, C12, C13) \qquad \dots (2)$$

$$D_{ij} = (C11, C22, C23, C32, C33) \qquad \dots (3)$$

These coefficients represents the directionality of the image and they represent the higher energy level in the DCT domain.Moreover, there is no computation involved in this as the logic is only behind picking the right set of values for similarity matching. We also add the statistical texture features to this as an additional set for improved efficiency. This include:

$$\text{Skew} = (1/(\text{std.dev})^3) \sum (b - \text{mean})^3\, p(b) \text{ where b varies from 1 to L} \qquad \dots (4)$$

Here p(b) corresponds to probability distribution of bin b in the Y plane.

$$P(b) = H(b) / M \qquad \dots (5)$$

Here M represents the number of blocks in the input image I
Similarly, mean is given by:

$$\text{Mean} = \sum b\, p(b) \qquad \dots (6)$$

The standard deviation on the other hand is given as:

$$\text{Std.Dev} = \text{SQR.Root} \left(\sum (b - \text{mean})^2\, p(b)\right) \qquad \dots (7)$$

The skew represent the third order moment while the kurtosis represents the fourth order moment, which is also added in our feature set as:

$$\text{Kurtosis} = (1/(\text{std.dev})^4) \sum (b - \text{mean})^4\, p(b) \qquad \dots (8)$$

The last parameter is the entrophy, which provides the randomness of the distribution of the coefficients values over the intensity ones. It is given by:

$$\text{Entrophy} = - \sum p(b) \log_2[p(b)] \qquad \dots (9)$$

All these features put together form our texture feature set which is further used for image retreival purposes.

4.4. Adapted Huffman and Qunatization table from JPEG header

The header part in a JPEG image contains multiple segments including a marker, which helps in identifying the segment. Of all the different components involved in the header portion, we are interested only in the Huffman and the quantization table segments. These help us in filtering the images at the first level and reduce the data set before further similarity matching.

5. Support Vector Machine for Relevance feedback mechanism

User Query Concept is an idea in image retrieval that deals with the images, which the system user is looking for.Query concept is normally semantic and this leads to sematic gap, which is a major problem in image retreival system and that, can be bridged to some extent through several mechanisms. By means of segmenting the images in to smaller pieces and then naming the individual parts, we can reduce this gap, which is a traditional approach. Relevance feedback is another approach where the user provides feedback either knowingly or unknowingly which helps to improve the performance of the system. We take the second approach in this research work for its advantages and the encouraging results[30][32].

Ranking methods like L1 and L2 norms are sufficient for single query images while the image retrieval systems mostly deal mostly with multiple query images pushing the need for powerful machine learning algorithms like Support Vector Machines (SVM). Training and testing are the two phases involved in any machine-learning algorithm. The goal is to design a hyperplane that classifies all the training vectors in two classes and then update it every time based on the user feedback. This is represented in Fig 1.4.

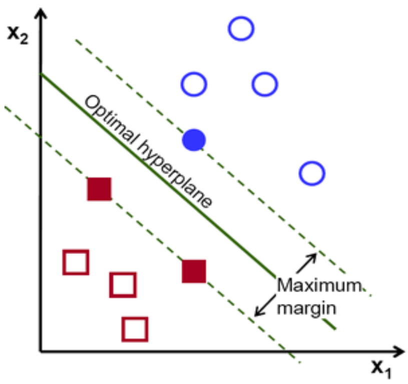

Fig 1.4: (a) SVM support in deciding optimal hyperplane

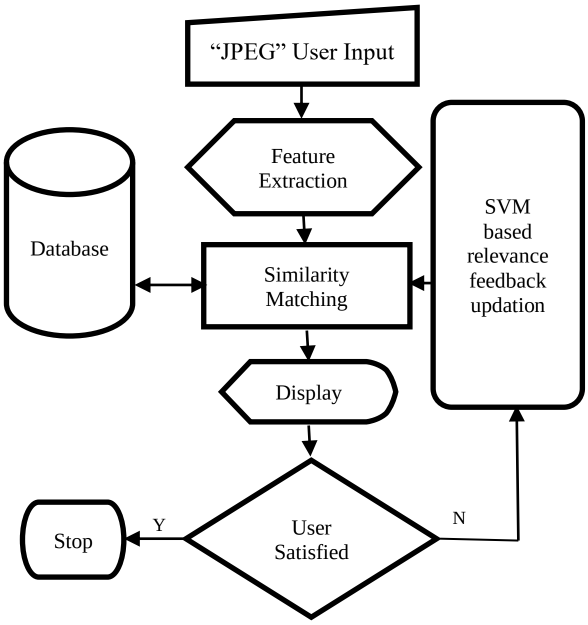

Fig 1.4: (b) SVM based relevance feedback in refining CBIR results

The equation below represents the hyperplanes that helps in separation of two classes of data and hence called as bilinear classifier.

$$w^T x - b = 1 \text{ and } w^T x - b = -1 \qquad (10)$$

Minimizing this weight vector w is a non-linear optimization task that is solved by Karush-kuhn-Tucker (KKT) conditions, using Langrange multipliers λ_i, which is given by

$$w = \sum \lambda_i y_i x_i \text{ and } \sum \lambda_i y_i = 0 \text{ where i varies from 0 to n} \qquad (11)$$

Support vectors are the data points that are nearest to the hyperplane and they are the critical elements of a data set, which helps in building the SVM. The decision function is given by

$$x^T = \mathrm{Sign}(w^T x - b) \qquad (12)$$

For non-linear functions, the kernel trick avoids the explicit mapping needed for linear learning algorithms to find the decision boundary. They help to operate in high-dimensional, implicit feature space without increasing the computational complexity. Once the images are trained with the vectors in the feature space, the precision – recall values are found during the testing phase. We introduce relevance feedback at this stage for iterative improvement until we reach a point of diminishing returns. The learning limitation of a classifier will make us to stop on further weight adjustment.

We also use tf-idf method in adjusting the weights of the feature vectors during this iterative feedback mechanism. The tf parameter captures the number of features described by a visual word. The frequency of visualword in the image provides useful data about recurrent textures and structures. Theidf part on the other hand provides the informativeness of visual words – visual words that are present in different images are less informative than those that appear rarely.

Search engines like CBIR systems uses variations of tf-idf weighting scheme as a central tool in ranking a pictures relevance for the user query. A weighted score is calculated and assigned based on this feedback mechanism and the system is then trained again to find a new set of support vectors with the new adjusted weights. This in turn helps to improve the CBIR system performance[31].

6. Results and Discussion

Extensive experiments were conducted on the proposed algorithm using the COREL image database. The 10K dataset contains 100 categories with close to 10000 images from different domains including beaches, flowers, buildings, sunset, cars, animals, mountains and houses to name a few as shown in Fig 1.5. The image size is 192*128 or 128*192 and in JPEG format which is most needed for the proposed methodology. We developed a CBIR system using MATLAB programming language.

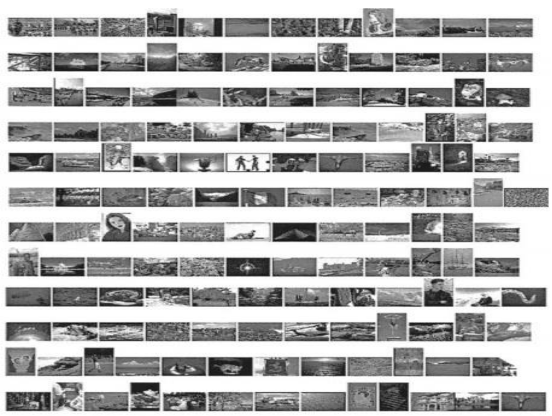

Fig 1.5: Snapshot of the COREL image dataset

Each feature vector is composed of 9 features including color hue, saturation, texture properties, skewness, kurtosis, entrophy and JPEG header information. Precision, Recall and F-measure are used in performance measurement of the system. They are given by:

Precision = Number of relevant images retrieved / Number of images requested

Recall = Number of images retrieved / Number of images requested

F-measure = Harmonic mean of Precision and Recall i.e. 2RP / (R+P)

To elaborate the proposed system performance, we have randomly selected training and test images from the database. We used MATLAB for our system design and implementation. The query image is provided by selecting one of the images randomly from the database. The results shown here are after obtaining the relevance feedback from the end user of the system. Table 1.1 represent the precision retrieval performance and Table 1.2 represent the recall values across the proposed JPEG and pixel domain methods. We have used methods from [23, 24 and 25] as these systems have their results on the common semantic categories of COREL database. Based on the retrieval accuracy it is clear that the proposed method is quite efficient compared to the methods in the literature.

Table2.1. Mean Precision comparison across different methods

Input Image	Proposed Method	[23]	[24]	[25]
Beach	0.83	0.53	0.56	0.7
Elephant	0.87	0.57	0.67	0.8
Flower	0.86	0.89	0.91	0.95
Mountain	0.78	0.51	0.53	0.75
Food	0.90	0.69	0.74	0.75
Mean	**0.85**	**0.64**	**0.68**	**0.79**

Table 3.2: Mean Recall comparison across different methods

Input Image	Proposed Method	[23]	[24]	[25]
Beach	0.16	0.19	0.19	0.14
Elephant	0.17	0.15	0.15	0.16
Flower	0.17	0.11	0.11	0.19
Mountain	0.13	0.22	0.22	0.15
Food	0.18	0.13	0.13	0.15
Mean	**0.162**	**0.16**	**0.16**	**0.158**

We have implemented and compiled all the proposed algorithms with GCC compiler on Intel Core 2 Duo 2.66GHz CPU under the Windows operating system. It is also clear from the table 1.3 that the time taken to publish the retrieval results is much faster when compared with the other methods as discussed in [26].

Table 4.3: Mean Retreival time across different methods

Different CBIR Methods	Retrieval Time in msec
MPEG-7 Scalable Color	75985
MPEG-7 Color Layout	30499
Color indexing	18746
Schaefer	7486
Lay and Guan	7448
Proposed Method	**1245**

From the above table 1.3, it is clear that the pixel domain methods takes a significantly large time for retreival while the proposed method reduces the computational complexity as there is no need to perform inverse discrete cosine transformation in this method and the features are extracted directly in the DCT domain itself. Reading the JPEG header is also faster and the proposed method takes a mere 16% of the time of the next fastest algorithm.

7. Future Directions

Despite the different research methodologies in the past decade on image retreival, there is still scope of improvement in terms of semantic gap filling and retreival accuracy along with the reduced time. In this work, we have proposed novel methods for addressing these issues and there is scope of extending the solution to the other multimedia domain including the video image retreival and graphical image processing. The idea can also be looked towards DWT based compressed images as used in JPEG 2000 coding standard. Also for semantic-aware retrieval, deep learning methods like supervised or semi-supervised methods needs to be more tuned.

References

[1] Baisakhi Sur Phadikar, Amit Phadikar and Goutam Kumar Maity, Content-based image retrieval in DCT compressed domain with MPEG-7 edge descriptor and genetic algorithm, G.K. Pattern Anal Applic (2016).

[2] FazalMalik and BaharumBaharudin, Analysis of distance metrics in content-based image retrieval using statistical quantized histogram texture features in the DCT domain, Journal of King Saud University - Computer and Information Sciences, Volume 25, Issue 2, July 2013, Pages 207-218.

[3] David Edmundson, Gerald Schaefer, Exploiting JPEG Compression for Image Retrieval, IEEE International Symposium on Multimedia, 2012, DOI: 10.1109/ISM.2012.99.

[4] Zhe-Ming Lu, Su-Zhi Li and Hans Burkhardt, A Content based image retreival scheme in JPEG compressed domain, International Journal of Innovative Computing, Information and Control, August 2006.

[5] LokeshSetia, Julia Ick and Hans Burkhardt, SVM-based Relevance Feedback in Image Retrievalusing Invariant Feature Histograms, In Proc. of the IAPR Workshop on Machine Vision Applications, 2005.

[6] Jun Yue, Li, Liu and Fu. Content-based image retrieval using color and texture fused features.Mathematical and Computer Modelling, Volume 54, Issues 3–4, August 2011, Pages 1121–1127.

[7] Arnold W. M. Smeulders, Worring, Santini, Amarnath Gupta and Jain, Content-Based Image Retrieval at the End of the Early Years, IEEE Transactions on Pattern Analysis and Machine Intelligence archive, Volume 22 Issue 12, 2000, Page 1349-1380

[8] RaghupathiGali, M. L. Dewal and R. S. AnandGenetic Algorithm for Content Based Image Retrieval, 4th International Conference onComputational Intelligence, Communication Systems & Networks 2012.

[9] Hee-Jung Bae and Sung-Hwan Jung, Image retrieval using texture based on DCT, Proceedings of 1997 International Conference onInformation, Communications and Signal Processing, 1997.

[10] K. Satya Sai Prakash and RMD. Sundaram, Combining Novel features for Content Based Image Retrieval, 14th International Workshop on Systems, Signals and Image Processing, 2007 and 6th EURASIP Conference focused on Speech & Image Processing, Multimedia Communications & Services.

[11] Ebroul Izuierdo and Qianni Zhang, Senior Member, IEEE, Histology Image Retrieval in Optimized Multifeature Spaces, IEEE Journal of Biomedical and Health Informatics, VOL. 17, NO.1, January 2013

[12] Padmashri Suresh, R. M. D. Sundaram and Aravindhan Arumugam, Feature Extraction in Compressed Domain for Content Based Image Retrieval, International Conference on Advanced Computer Theory and Engineering, 2008. ICACTE '08.

[13] Gerald Schaefer, Pixel domain and compressed domain image retrieval features, Eighth International Conference onDigital Information Management (ICDIM), 2013.

[14] Abhishek, S.N., Shriram K Vasudevan and Sundaram, R.M.D., An enhanced and efficient algorithm for faster, better and accurate edge detection, Communications in Computer and Information Science, Springer Verlag, Volume 679, p.24-41 (2016).

[15] W. H. Hsu, L. S. Kennedy and S.-F. Chang. Reranking Methods for Visual Search. IEEE Multimedia, vol. 14, no. 3, pp. 14-22, 2007

[16] B. Chellaprabha and RMD. Sundaram, Effective Video Streaming Using Reset-Controlled DCCP along with Data Quality Analysis, Asian Journal of Information Technology, Year: 2016 | Volume: 15 | Issue: 20 | Page No.: 3986-3990

[17] Xia Wu,Based on the Characteristics of the JPEG Image Retrieval System Research, Seventh International Conference onMeasuring Technology and Mechatronics Automation (ICMTMA), 2015.

[18] PrafullaBafna, DhanyaPramodandAnagha Vaidya, Document clustering TF-IDF approach, International Conference onElectrical, Electronics, and Optimization Techniques (ICEEOT), 3-5 March 2016, DOI: 10.1109/ICEEOT.2016.7754750.

[19] Yu Suzuki, Masahiro Mitsukawa andKyoji Kawagoe, A Image Retrieval Method Using TFIDF Based Weighting Scheme, 19th International Workshop onDatabase and Expert Systems Application, 2008.

[20] Bin Li, Ng, Xiaolong Li, Tan and Huang, Revealing the Trace of High-Quality JPEG Compression Through Quantization Noise Analysis, IEEE Transactions: Information Forensics & Security, March 2015.

[21] T. Dharani and I. Laurence Aroquiaraj, A survey on content based image retrieval, International Conference onPattern Recognition, Informatics and Mobile Engineering (PRIME), 2013.

[22] Wengang Zhou, Houqiang Li and Qi Tian, Recent Advance in Content-based Image Retrieval: A Literature Survey, electronic edition @ arxiv.org, 2017.

[23] M. B. Rao, B. P. Rao, and A. Govardhan, Content based image retrieval system based on dominant color and texture features,International Journal ofComputer Applications, Vol. 18, 2011 pp. 40-46.

[24] M. E. ElAlami, A novel image retrieval model based on the most relevant features, Knowledge-Based Systems, Vol. 24, 2011, pp. 23-32.

[25] R. Ashraf, K. Bashir, A. Irtaza, and M. T. Mahmood, Content based image retrieval using embedded neural networks with bandletized regions, Entropy, Vol. 17, 2015,pp. 3552-3580.

[26] David Edmundson and Gerald Schaefer, Fast JPEG Image Retrieval using Optimised Huffman Tables, 21st International Conference on Pattern Recognition (ICPR 2012)November 11-15, 2012. Tsukuba, Japan

[27] Alexandra S. Teynor, Image Retrieval in the Compressed Domain Using JPEG2000, Diploma Thesis for the Multimedia course of study at Department of Computer Science in Augsburg University of Applied Sciences.

[28] Vimal, S., Kalaivani, L. & Kaliappan, Collaborative approach on mitigating spectrum sensing data hijack attack and dynamic spectrum allocation based on CASG modeling in wireless cognitive radio networks, M. Cluster Computing (2017),https://doi.org/10.1007/s10586-017-1092-0.

[29] Vimal.s, et al., “Secure data packet transmission in MANET using enhanced identity-based cryptography”. International Journal of New Technologies in Science and Engineering Vol. 3, 2016,No.12, pp.35-42.

[30] Kannan, N., Sivasubramanian, S., Kaliappan, M. et al. Cluster Comput (2018). https://doi.org/10.1007/s10586-018-2384-8.

[31] Mariappan, E., Kaliappan, M., Vimal, S.: Energy efficient routing protocol using Grover’s searching algorithm for MANET. Asian J. Inf. Technol. 15, 4986–4994. https://doi.org/10.3923/ajit.2016.4986.4994 (2016)

[32] Ilango, S.S., Vimal, S., Kaliappan, M. et al. Cluster Comput (2018). https://doi.org/10.1007/s10586-017-1571-3