IJDACR
ISSN: 2319-4863

International Journal of Digital Application & Contemporary Research

International Journal of Digital Application & Contemporary Research
Website: www.ijdacr.com (Volume 4, Issue 10, May 2016)

Neural Network Based Query Image Extraction using Shape, Color and Texture Features

Amreen Syed
amreen222.syed@gmail.com

Sourabh Jain
sourabhjain@ipsacademy.org

Abstract –**Content-based image retrieval (CBIR) is the application of computer vision to the image retrieval problem, that is, the problem of searching for digital images in large databases. Most of the existing image retrieval systems give lesser accuracy while using different features individually. Therefore, in this paper, we develop a framework using extraction of color, texture and shape features along with Neural Network Classifier to classify the extracted features. For similarity measurement, we have used Euclidian distances for each feature. Performance of the proposed research work is carried out using certain evaluation parameters, namely; False Negative Rate, False Positive Rate, True Positive Rate and True Negative Rate.**

Keywords – **CBIR, Neural Network, False Negative Rate, False Positive Rate, True Positive Rate and True Negative Rate.**

I. Introduction

The area of image retrieval has been a dynamic exploration range for a few decades and has been given careful consideration lately as a consequence of the dramatic and quick increment in the use of digital images. The improvement of Internet not just cause a violently increasing volume of digital images, additionally give individuals more approaches to get those images. The vitality of a viable strategy in searching and retrieving images from huge collection can't be overemphasized. One methodology for indexing and recovering image information is utilizing manual content annotations. The annotations can then be utilized to search images by implication. Yet there are a few issues with this methodology. Initially, it is extremely hard to portray the contents of an image utilizing just a couple of keywords. Second, the manual annotation procedure is exceptionally subjective, uncertain, and deficient. Those issues have made incredible requests for automatic and compelling procedures for content-based image retrieval (CBIR) frameworks. Most CBIR frameworks utilize low-level image features, for example, color, texture, shape, edge, and so on, for image indexing and retrieval. This is on account of the low-level features can be processed automatically.

Ongoing expansion of digital images requires improved methods for sorting, browsing, and searching through ever-growing image databases. Such databases are used by various professionals including doctors searching for similar clinical cases, editors looking for illustration images and almost everyone needs to organise their personal photos. Other applications comprise accessing video archives by means of similar key frames, detection of unauthorised image use, or cultural heritage applications. Former approaches to the image indexation were based on text descriptions and suffered not only from laborious and expensive creation but also imprecise description. Textual descriptions are influenced by personal background and expected utilisation, which is difficult or even impossible to predict. Moreover, there are some properties that can be hardly described in text as the atmosphere of Edvard Munch's The Scream.

Content-Based Image Retrieval (CBIR) systems are search engines for image databases, which index images according to their content. A typical task solved by CBIR systems is that a user submits a query image or series of images and the system is required to retrieve images from the database as similar as possible. Another task is a support for browsing through large image databases, where the images are supposed to be grouped or organised in accordance with similar properties. Although the image retrieval has been an active research area for many years (Smeulders et al. (2000) [1] and Datta et al. (2008) [2]) this difficult problem is still far from being solved. There are two main reasons, the first is so called semantic gap, which is the difference between information that can be extracted from the visual data and the interpretation that the same data have for a user in a given situation. The other reason is called sensory gap, which is the difference between a real object and its computational representation derived from sensors, which measurements are significantly influenced by the acquisition conditions.

IJDACR
ISSN: 2319-4863

IJDACR
International Journal Of Digital Application & Contemporary Research

International Journal of Digital Application & Contemporary Research
Website: www.ijdacr.com (Volume 4, Issue 10, May 2016)

The semantic gap is usually approached by learning of concepts or ontologies and subsequent attempts to recognise them. A system can also learn from the interaction with a user or try to employ combination of multimedia information. However, these topics are beyond the scope of this work and we refer to reviews Smeulders et al. (2000) [1] and Lew et al. (2006) [3] for further information.

II. Existing CBIR Systems

Early CBIR systems as QBIC (Flickner et al., 1995) [4] and VisualSEEk (Smith and Chang, 1996) [5] were based on image colours represented by a kind of colour histogram, which totally ignored structures of materials and object surfaces present in the scene. Visual appearances of such structured surfaces are commonly referred as textures and their characterisation is essential for understanding of real scene images.

Later systems attempted to include some textural description, e.g. based on wavelets as CULE (Chen et al., 2005) [6], IBM Video Retrieval System (Amir et al., 2005) [7] or Gabor features as MediaMill (Snoek et al., 2008) [8]. MUFIN (Batko et al., 2010) [9], which is focused on efficiency and scalability, includes a simple texture representation by MPEG-7 descriptors. A CBIR system (Anaktisi) (Chatzichristofis et al., 2010) [10] is aimed at a compact representation, which was extracted by fuzzy techniques applied to colour features and wavelet based texture description. However, texture representations in these systems are more or less supplemental and the algorithms rely on colour features. Although retrieval results look promising, they are often provided by enormous image databases than exact image indexing. It is quite simple to fill the first result page with very similar images from a large database (e.g. sunsets, beaches, etc.), nevertheless, the lack of image understanding is revealed on further result pages.

In narrow image domains, CBIR systems are more successful e.g. trademark retrieval (Leung and Chen, 2002 [11]; Wei et al., 2009 [12]; Phan and Androutsos, 2010 [13]), drug pill retrieval (Lee et al., 2010) [14] or face detection (Lew and Huijsmans, 1996) [15] and similarity, which evolved in a separate field.

One of the reasons of disregarding textural features are that they are still immature for a reliable representation (Deselaers et al., 2008) [16] and at least weak texture segmentation of images is required (Smeulders et al., 2000) [1]. If the segmentation is extracted, shape features and region relations can be employed (Datta et al., 2008) [2], however, the reliable segmentation is a difficult problem on its own. Recent methods avoid the image segmentation by local descriptors as SIFT (Lowe, 2004) [17], which were extended to colour images and used for image indexing (van de Sande et al., 2010 [18]; Burghouts and Geusebroek, 2009a [19]; Bosch et al., 2008 [20]). However these key point based descriptors are more suitable for description of objects without large textured faces than homogeneous texture areas.

The other reason for marginalising textures is that a more precise description of textures also requires more attention to expected variations of acquisition conditions. Many existing systems do not care about such variations or they handle it in a very limited way.

III. Proposed Method

Figure 1 exhibits the proposed approach used in this research work:

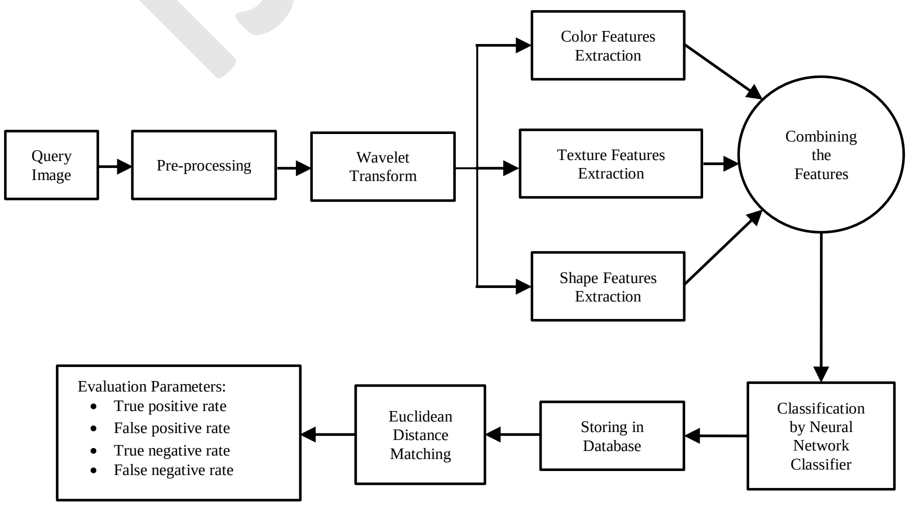

Figure 1: Basic Block Diagram for Proposed Research Work

IJDACR International Journal Of Digital Application & Contemporary Research

International Journal of Digital Application & Contemporary Research
Website: www.ijdacr.com (Volume 4, Issue 10, May 2016)

This research work intends a novel content based image retrieval framework utilizing color, texture and shape features. Initially, a query image is selected arbitrarily from the database. Since the database contains images of different dimensions. To extract certain features from the image, it is necessary to reduce the dimensions of the selected image. Pre-processing is applied to lessen the dimension of selected image trailed by discrete wavelet transform. The next step is to extract certain features from image which are as follows:

Color Features Extraction

RGB to HSV Conversion

An image pixel value is converted from the RGB representation using the formula shown below:

$$H = \cos^{-1}\frac{\frac{1}{2}[(R-G)+(R-B)]}{\sqrt{(R-G)^2+(R-B)(G-B)}} \quad (1)$$

$$S = 1-\frac{3[\min(R,G,B)]}{R+G+B} \quad (2)$$

$$V = \left[\frac{R+G+B}{3}\right] \quad (3)$$

Color Moments

a. Mean
b. Standard Deviation

If the value of the i^{th} color channel at the j^{th} image pixel is I_{ij} and the number of pixels is N, then the index entries related to this color channel and the region 'r' are known as the color moments followed by the formula:

a. Mean:

$$E_{r,i} = \frac{1}{N}\sum_{j=1}^{N} I_{ij} \quad (4)$$

b. Standard Deviation:

$$\sigma_{r,i} = \sqrt{\frac{1}{N}\sum_{j=1}^{N}\left(I_{ij}-E_{r,i}\right)^2} \quad (5)$$

Where $E_{r,i}$ $(1 \le i \le 3)$ represents the average color (mean) of the region r and $\sigma_{r,i}$ represents the standard deviation of the region r. And the extracted color features are given by the following feature vector:

$$f_c = \{E_{1,1},\sigma_{1,1}E_{2,2},\sigma_{2,2}E_{3,3},\sigma_{3,3}\dots\dots\dots\dots\dots.E_{r,i},\sigma_{r,i}\} \quad (6)$$

Texture Features Extraction

For a given image $I(x,y)$ having size $P\times Q$, the discrete Gabor wavelet transform is expressed by the following convolution:

$$G_{mn}(x,y) = \sum_s\sum_t I\,(x-s,y-t)\psi_{mn}^{*}(s,t) \quad (7)$$

Where, s and t are the filter mask size variables, and ψ_{mn}^{*} is the complex conjugate of ψ_{mn}.

$$\psi(x,y) = \frac{1}{2\pi\sigma_x\sigma_y}\exp\left[-\frac{1}{2}\left(\frac{x^2}{\sigma_x^2}+\frac{y^2}{\sigma_y^2}\right)\right].exp(j2\pi Wx) \quad (8)$$

Where W denotes the modulation frequency. Now the generating function:

$$\psi_{mn}(x,y) = a^{-m}\psi(\tilde{x},\tilde{y}) \quad (9)$$

Where m and n specify the scale and orientation of the wavelet respectively.

And $m = 0,1,\dots M-1, n = 0,1,\dots,N-1$, and

$$\tilde{x} = a^{-m}(x\cos\theta + y\sin\theta) \quad (10)$$

$$\tilde{y} = a^{-m}(-x\sin\theta + y\cos\theta) \quad (11)$$

Where $a > 1$ and $\theta = n\pi/N$.

And,

$$a = (U_h/U_l)^{\frac{1}{M-1}} \quad (12)$$

$$W_{m,n} = a^m U_l \quad (13)$$

$$\sigma_{x,m,n} = \frac{(a+1)\sqrt{2\ln 2}}{2\pi a^m(a-1)U_l} \quad (14)$$

$$\sigma_{y,m,n} = \frac{1}{2\pi\tan\left(\frac{\pi}{2N}\right)\sqrt{\frac{U_h^2}{2\ln 2}-\left(\frac{1}{2\pi\sigma_{x,m,n}}\right)^2}} \quad (15)$$

Wavelet Moments

In the wake of applying Gabor filters on the picture with distinctive orientation at diverse scale, we acquire following array [21]:

$$E(m,n) = \sum_x\sum_y|G_{mn}(x,y)| \quad (16)$$

Where, $m = 0,1,\dots,M-1$; $n = 0,1,\dots,N-1$

It is assumed that we are interested in images or regions that have homogenous texture, therefore the mean and standard deviation are expressed as [21]:

$$\mu_{mn} = \frac{E(m,n)}{P\times Q} \quad (17)$$

$$\sigma_{mn} = \frac{\sqrt{\sum_x\sum_y(|G_{mn}(x,y)|-\mu_{mn})^2}}{P\times Q} \quad (18)$$

A feature vector f_g (texture representation) is created using μ_{mn} and σ_{mn} as the feature components [21, 22]:

$$f_g = (\mu_{00},\sigma_{00},\mu_{01},\sigma_{01}\dots\dots.\mu_{45},\sigma_{45}) \quad (19)$$

Shape Features Extraction

Shape is an imperative visual feature and it is one of the essential features used to portray content of a picture. Though, shape representation and portrayal is a hectic process. This is on the grounds that when a 3-D real world object is anticipated onto a 2-D picture plane, one measurement of object data is misplaced. Subsequently, the shape extracted from the picture partially shows to the anticipated item.

The shape features are extracted using the edge histogram descriptor (EHD). It represents the local edge distribution by dividing image space into 4×4 sub-images and representing the local distribution of each sub-image by a histogram. The fact that the EHD consists of the local-edge histograms only, makes it very flexible.

IJDACR
ISSN: 2319-4863

IJDACR
International Journal Of Digital Application & Contemporary Research

International Journal of Digital Application & Contemporary Research
Website: www.ijdacr.com (Volume 4, Issue 10, May 2016)

Vertical | Horizontal | 45 Degree | 135 Degree | Non-Directional

Figure 2: Five types of edges in the edge histogram descriptor

To generate the histogram, edges in the sub-images are categorized into five types; vertical, horizontal, 45-degree diagonal, 135-degree diagonal and non-directional edges (Figure 2). Each sub-image is further divided into non-overlapping square image blocks with particular size which depends on the image resolution. Every single block of the image is then classified into one of the five specified edge classifications or as a non-edge block. A simple method to do this classification is to treat each image-block as a 2×2 super-pixel image-block and apply appropriate oriented edge detectors to compute the corresponding edge strengths. The edge detector with maximum edge strength is then identified. If this edge strength is above a given threshold, then the corresponding edge orientation is associated with the image-block. If the maximum of the edge strengths is below the given threshold, then that block is not classified as an edge block.

Histogram of Edge Directions

The edge histogram is computed as follows. At first, the color image is transformed to the HSI space from which the hue channel is neglected. The resulting gradient images are next thresholded to binary images by a proper threshold value for each channel. The threshold values are manually fixed to certain levels which are the same for all images. The thresholded intensity and saturation gradient images are combined by the logical OR operation. The threshold value for the intensity gradient image was manually set to 15% of the maximum gradient value and for the saturation image to 35%. In the OR operation, the direction of the larger gradient value is chosen. Finally the 8-dimensional edge histograms are calculated by counting the edge pixels in each direction. The smoothing should make the histograms more robust to rotation. It is performed as follows:

$$H^s(i) = \frac{\sum_{l=i-k}^{i+k} H(l)}{2k+1} \qquad (20)$$

Where $H(l)$ stands for the original edge histogram and the degree of smoothing is regulated by the parameter k.

Color Histogram

Each one picture in the database is figured to acquire the color histogram, which demonstrates the extent of pixels of each one color inside the picture. The color histogram of each image is then stored in the database. When the user does the search by specifying the query image, the system registers the proportion of each color of the query image and goes through all images in the database to find those whose color histograms match those of the query most closely. The color histograms are utilized to speak to the color distribution in a picture. For the most part, the color histogram methodology checks the quantity of events of every extraordinary color on a specimen picture. Since a picture is made out of pixels and every pixel has a color, the color histogram of a picture can be processed effortlessly by going by every pixel once. By looking at the color histogram of a picture, the colors existing on the picture can be related to their relating regions as the quantity of pixels. Histogram search portrays a picture by its color distribution, or histogram. Euclidian histogram separations have been utilized to characterize the comparability of two color histogram representations.

Classification Using Neural Network

Back Propagation Neural Network (BPNN) generates complex decision boundaries in feature space. BPNN in specific circumstances resembles Bayesian Posterior Probabilities at its output. These conditions are essential to achieve low error performance for given set of features along with selection of parameters such as training samples, hidden layer nodes and learning rate. In else case, the performance of BPNN could not be evaluated. For W number of weights and N number of nodes, numbers of samples (m) are depicted to correctly classify future samples in following manner:

$$m \geq O\left(\frac{W}{\epsilon}\log\frac{N}{\epsilon}\right) \qquad (21)$$

The theoretical computation of number of hidden nodes is not a specific process for hidden layers. Testing method is commonly entertained for selection of these followed in the constrained environment of performance [23].

Back-Propagation Algorithm

The backpropagation algorithm for a 3-layer network (only one hidden layer) is as follows:

initialize the weights in the network (often small random values)
do
    for *each image i in the training set of*
      database O = neural-network-output(network, i)
      T = desired output for i
      calculate error (T - O) at the output units;
      calculate δ_h for all weights from hidden layer

IJDACR
ISSN: 2319-4863

IJDACR
International Journal Of Digital Application & Contemporary Research

International Journal of Digital Application & Contemporary Research
Website: www.ijdacr.com (Volume 4, Issue 10, May 2016)

to output layer;
calculate δ_i for all weights from input layer to hidden layer;
update the weights to minimize error in the network; ***until*** *some stopping criterion satisfied*
return *the network*

Algorithm for Proposed Work

The testing phase include the querying and retrieving task. The query image is first pre-processed and also its features are extracted. The trained network is presented with query image features. The network, acting as a classifier, selectively retrieves top matched, relevant, similar images as that of query image from the database and are presented to user. The algorithm for proposed CBIR system can be given as follows:

Algorithm for Training Phase

Setup ANN and initialize the following parameters as:
number_of_layers= 3; epochs=1000; learning_rate=80%; permissible_error=0.03;
input: *network,*
training set ***do***
for *each image in training set*
extract its color features using color histogram algorithm;
extract its edge features using edge histogram algorithm;
extract its texture features using discrete gabor wavelet transform algorithm;
fuse the extracted features into a single features matrix;
until *a single feature vector matrix is built;* ***do***
train the network about class labels and feature vectors;
until *stopping criterion epochs=1000 is satisfied*
output: *a trained neural network*

Algorithm for Testing Phase

input: *a query image.*
load the input query image;
extract its color, edge and texture features; load the fused features database;
compute similarity between query image features and training set features;
output: *set of similar images if present; if not, display "No similar images found"*

IV. Simulation And Results

The performance of proposed algorithms has been studied by means of MATLAB simulation.

Figure 3: Retrieved image from database

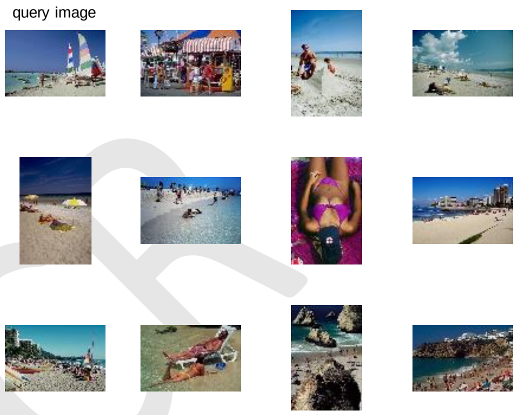

Figure 4: Retrieved image from database

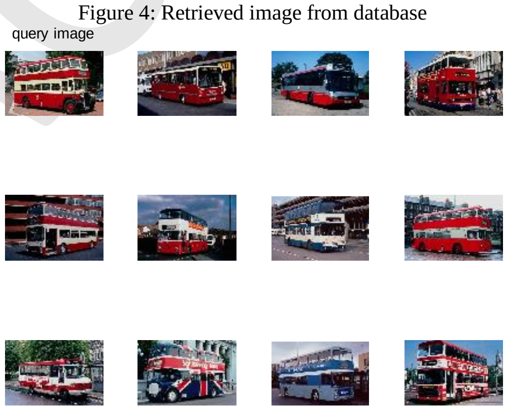

Figure 5: Retrieved image from database

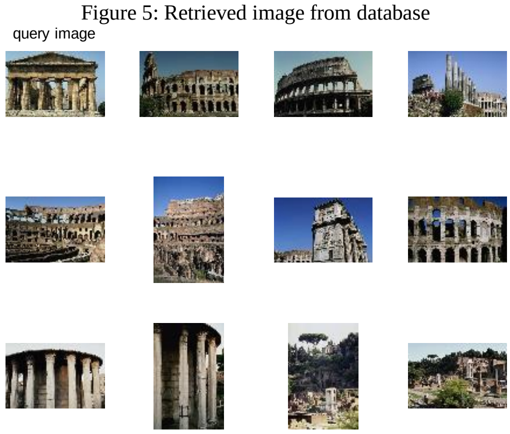

Figure 6: Retrieved image from database

IJDACR
International Journal Of Digital Application & Contemporary Research

International Journal of Digital Application & Contemporary Research
Website: www.ijdacr.com (Volume 4, Issue 10, May 2016)

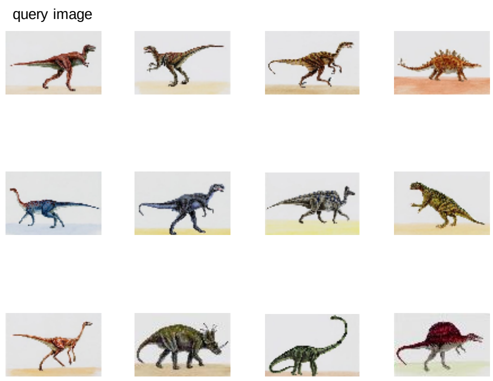

Figure 7: Retrieved image from database

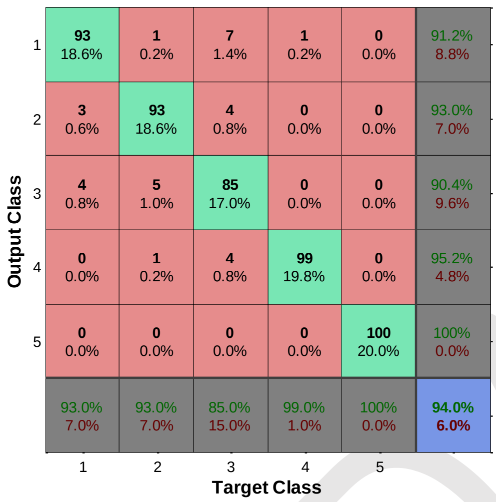

Figure 8: Confusion matrix between output class and target class

Table 1: Performance Evaluation

Class	Category	False Negative Rate	False Positive Rate	True Positive Rate	True Negative Rate
1	Africa	0.0176	0.0882	0.9118	0.9824
2	Beach	0.0175	0.0700	0.9300	0.9825
3	Transportation	0.0369	0.0957	0.9043	0.9631
4	Architecture	0.0025	0.0481	0.9519	0.9975
5	Dinosaur	0	0	1.0000	1.0000

V. Conclusion

The algorithm has been implemented and tested using 500 COREL color images and find out the retrieval performance on the basis of evaluation parameters; False Negative Rate, False Positive Rate, True Positive Rate and True Negative Rate. The experimental result shows that the proposed method outperforms better results in terms of evaluation parameters. The confusion matrix plot indicates the accuracy i.e. 94.0% for proposed approach.

Reference

[1] A. W. Smeulders, M. Worring, S. Santini, A. Gupta, and R. Jain. , "Content-based image retrieval at the end of the early years". IEEE Transactions on Pattern Analysis and Machine Intelligence, 22(12):1349-1380, 2000. ISSN 0162-8828. doi: 10.1109/34.895972.

[2] Datta, D. Joshi, J. Li, and J. Z. Wang. , "Image retrieval: Ideas, influences, and trends of the new age". ACM Computing Surveys, 40(2):1-60, 2008. ISSN 0360-0300. doi: 10.1145/1348246.1348248.

[3] M. S. Lew, N. Sebe, C. Djeraba, and R. Jain. , "Content-based multimedia information retrieval: State of the art and challenges". ACM Transactions on Multimedia Computing, Communications and Applications, 2(1):1-19, 2006. ISSN 1551-6857. doi: 10.1145/1126004.1126005.

[4] M. Flickner, H. Sawhney, W. Niblack, J. Ashley, Q. Huang, B. Dom, M. Gorkani, J. Hafner, D. Lee, D. Petkovic, D. Steele, and P. Yanker. "Query by image and video content: the QBIC system". Computer, 28(9):23-32, September 1995. ISSN 0018-9162. doi: 10.1109/2.410146.

[5] J. R. Smith and S.-F. Chang. "VisualSEEk: a fully automated content-based image query system". In Proceedings of the fourth ACM international conference on Multimedia, MULTIMEDIA 1996, pages 87-98, New York, NY, USA, 1996. ACM. ISBN 0-89791-871-1. doi: 10.1145/244130.244151.

[6] Y. Chen, J. Z. Wang, and R. Krovetz. "CLUE: Cluster-based retrieval of images by unsupervised learning". IEEE Transactions on Image Processing, 14(8):1187-1201, August 2005. doi: 10.1109/TIP.2005.849770.

[7] A. Amir, J. Argillander, M. Campbell, A. Haubold, G. Iyengar, S. Ebadollahi, F. Kang, M. R. Naphade, A. P. Natsev, J. R. Smith, J. Tesic, and T. Volkmer. IBM research TRECVID-2005, "video retrieval system". In NIST TRECVID-2005 Workshop, Gaithersburg, November 2005.

[8] C. G. M. Snoek, K. E. A. van de Sande, O. de Rooij, B. Huurnink, J. van Gemert, J. R. R. Uijlings, J. He, X. Li, I. Everts, V. Nedovic, M. van Liempt, R. van Balen, M. de Rijke, J.-M. Geusebroek, T. Gevers, M. Worring, A. W. M. Smeulders, D. Koelma, F. Yan, M. A. Tahir, K. Mikolajczyk, and J. Kittler. The MediaMill TRECVID 2008 semantic video search engine. In P. Over, G. Awad, R. T. Rose, J. G. Fiscus, W. Kraaij, and A. F. Smeaton, editors, TRECVID. National Institute of Standards and Technology (NIST), 2008.

[9] M. Batko, F. Falchi, C. Lucchese, D. Novak, R. Perego, F. Rabitti, J. Sedmidubsky, and P. Zezula. "Building a web-scale image similarity search system". Multimedia Tools and Applications, 47(3):599-629, 2010. ISSN 1380-7501. doi: 10.1007/s11042-009-0339-z.

[10] S. A. Chatzichristofis, K. Zagoriz, Y. S. Boutalis, and N. Papamarkos. "Accurate image retrieval based on compact composite descriptor and relevance feedback information". International Journal of Pattern Recognition and Artificial Intelligence, 24(2):207-244, 2010. doi: 10.1142/S0218001410007890.

[11] W. H. Leung and T. Chen. "Trademark retrieval using contour-skeleton stroke classification". In Proceedings of IEEE International Conference on Multimedia and Expo, ICME 2002, volume 2, pages 517-520, 2002. doi: 10.1109/ICME.2002.1035662.

[12] C.-H. Wei, Y. Li, W.-Y. Chau, and C.-T. Li. "Trademark image retrieval using synthetic features for describing global shape and interior structure". Pattern Recognition, 42(3): 386-394, 2009. ISSN 0031-3203. doi: 10.1016/j.patcog.2008.08.019.

IJDACR International Journal Of Digital Application & Contemporary Research

International Journal of Digital Application & Contemporary Research
Website: www.ijdacr.com (Volume 4, Issue 10, May 2016)

[13] R. Phan and D. Androutsos. “Content-based retrieval of logo and trademarks in unconstrained color image databases using color edge gradient co-occurrence histograms”. Computer Vision and Image Understanding, 114(1):66-84, 2010. ISSN 1077-3142. doi: 10.1016/j.cviu.2009.07.004.

[14] Y.-B. Lee, U. Park, and A. K. Jain. “Pill-id: Matching and retrieval of drug pill imprint images”. In Proceedings of the 20th International Conference on Pattern Recognition, ICPR 2010, pages 2632-2635. IEEE, 23-26 August 2010. doi: 10.1109/ICPR.2010.645.

[15] M. Lew and N. Huijsmans. “Information theory and face detection”. In Proceedings of the 13th International Conference on Pattern Recognition, ICPR 1996, volume 3, pages 601-605. IEEE, 25-29 August 1996. doi: 10.1109/ICPR.1996.547017.

[16] T. Deselaers, D. Keysers, and H. Ney. “Features for image retrieval: an experimental comparison”. Information Retrieval, 11(2):77-107, 2008. ISSN 1386-4564. doi: 10. 1007/s10791-007-9039-3.

[17] D. G. Lowe. “Distinctive image features from scale-invariant keypoints”. International Journal of Computer Vision, 60(2):91-110, 2004. doi: 10.1023/B:VISI.0000029664. 99615.94.

[18] K. van de Sande, T. Gevers, and C. Snoek. “Evaluating color descriptors for object and scene recognition”. IEEE Transactions on Pattern Analysis and Machine Intelligence, 32(9):1582 -1596, sep. 2010. ISSN 0162-8828. doi: 10.1109/TPAMI.2009.154.

[19] G. J. Burghouts and J.-M. Geusebroek. “Material-specific adaptation of color invariant features”. Pattern Recognition Letters, 30:306-313, 2009b. doi: 10.1016/j. patrec.2008.10.005.

[20] A. Bosch, A. Zisserman, and X. Muoz. “Scene classification using a hybrid generative/ discriminative approach”. IEEE Transactions on Pattern Analysis and Machine Intelligence, 30(4):712-727, April 2008. ISSN 0162-8828. doi: 10.1109/TPAMI.2007. 70716.

[21] S. Mangijao Singh, K. Hemachandran, “Content-Based Image Retrieval using Color Moment and Gabor Texture Feature”, IJCSI International Journal of Computer Science Issues, Vol. 9, Issue 5, No 1, September 2012.

[22] B. S. Manjunath and W. Y. Ma. “Texture features for browsing and retrieval of large image data”, IEEE Transactions on Pattern Analysis and Machine Intelligence, (Special Issue on Digital Libraries), Vol. 18 (8), pp. 837-842, August 1996.

[23] Christos Stergiou and Dimitrios Siganos, “Neural Networks”, Report available at: http://www.doc.ic.ac.uk/~nd/surprise_96/journal/vol4/cs11/report.html