[Neutrosophic Sets and Systems](https://digitalrepository.unm.edu/nss_journal)

Volume 13 | Article 7

1-1-2016

Neutrosophic Features for Image Retrieval

A. A. Salama

Mohamed Eisa

Hewayda ElGhawalby

A.E. Fawzy

NSS

Neutrosophic Features for Image Retrieval

A.A.Salama[1], Mohamed Eisa[2], Hewayda ElGhawalby[3], A.E.Fawzy[4]

[1]*Port Said University , Faculty of Science, Department of Mathematics and Computer Science*
drsalama44@gmail.com
[2,4]*Port Said University , Higher Institute of Management and Computer, Computer Science Department*
mmmeisa@yahoo.com
[3]*Port Said University , Faculty of Engineering , Physics and Engineering Mathematics Department*
ayafawzy362@gmail.com

Abstract The goal of an Image Retrieval System is to retrieve images that are relevant to the user's request from a large image collection. In this paper, we present texture features for images embedded in the neutrosophic domain. The aim is to extract a set of features to represent the content of each image in the training database to be used for the purpose of retrieving images from the database similar to the image under consideration.

Keywords: Content-Based Image Retrieval (CBIR), Text-based Image Retrieval (TBIR), Neutrosophic Domain, Neutrosophic Entropy, Neutrosophic Contrast, Neutrosophic Energy, Neutrosophic Homogeneity.

1 Introduction

An Image Retrieval System is a computer system for searching and retrieving images from a large database of digital images. The traditional way to image retrieval is the text-based image retrieval (TBIR) which proposed late 1970s [17, 43]. Such techniques commence by annotating the images by text and then use text-based database management systems to retrieve images [8].
Although there are several progresses have been made to TBIR techniques. Such as data modeling. Multidimensional indexing, and query evaluation, there are some limitations when using such techniques. For instance, the problem of annotating images in large volumes of databases and that only one language is valid for image retrieval. Furthermore, the problems due to the subjectivity of human perception arising from the responsibility of the end-user; as well as the queries that cannot be described at all, but tap into the visual features of the image [2, 3, 4, 5].
Later on during the 1990's, another way was invented to retrieve images, which is Content-based Image Retrieval (CBIR) technique. The new techniques came up to deal with the rapid increase of using digital images databases on the internet. Used for retrieving, managing and navigating large digital images databases, the CBIR techniques index the images by their own visual content, such as color and texture, instead of annotated the image manually by text-based key words [11, 16, 22, 23, 36].
The Neutrosophic logic which proposed by Samarandache in [40] is a generalization of fuzzy sets which introduced by Zada at 1965 [45], The fundamental concepts of neutrosophic set, introduced by Samarandache in [41, 42] and Salama etl in [1, 14, 26, 27, 28, 29, 30, 31, 32, 33, 34, 35].

2 Image Retrieval Technique

2.1 Content-Based Image Retrieval (CBIR)

The Content-Based Image Retrieval was used to depict the experiments of automatic retrieval images from a database, that depended on colors and shapes. After that it used to retrieve images from a large collection of database based on syntactical image features. CBIR used some techniques, tools and algorithms which taken from some fields such as statistics, pattern recognition, signal processing and computer vision. In CBIR, the images indexed by the description of the visual content of the images. Most of the CBIR systems are concerned with the approximate queries, because it is aim to find the images visually similar to the target image. The target of CBIR system is to duplicate the human perception of image similarity as possible as it can.
Feature Extraction is the basic of CBIR. Features may contain both text-based features (key, words, annotations) and visual features (color, texture, shape, faces). The goal of feature extraction is to create high-level data (pixel

values). The visual features ordered in three levels: low level features (primitive), middle level features (logical) and high level features (abstract). All recently system were depended on low level features (color, shape). But now both mid-level and high-level image representations are in demand. The efficiency of a CBIR system depends on extracted features [6].

The stages of the CBIR process are:

1- Image acquisition: to acquire a digital image [9]. Image database: it consists of the collection of n number of images which depends on the user range and choice [9].
2- Image processing: it used to improve the image by increased the chances for success of the other processes. At first, the image processed to extract the features that depict its contents. This process contains filtering, normalization, segmentation, and object identification. For example, the process of image segmentation is used to divide an image into multiple parts and its output is a set of significant regions and objects [9].
3- Feature extraction: the features such as shape, texture, color are used to depict the content of the image. The features can be characterized as low-level and high-level features. The visual information in this step extracted from the image and saved as feature vector in a features database. The image description for each pixel is found in the form of feature vector by using the feature extraction. These feature vectors are used to make a compare between query with other images and retrieval [9].
4- Similarity matching: for each image, its information stored in its feature vectors for computation process and these feature vectors are matched with the feature vectors of query image to helps in similarity measure. This step contains the matching of the above stated features to have that is visually similar with the use of similarity measure method called as Distance method. There are another distance methods such as Euclidean distance, City block distance, Canberra distance [9].
5- Resultant retrieval images: this process searched for the prior maintained information to find the matched images from database. Its output will be the similar images with the same or very closest features as that of the query image [18].
6- User interface and feedback which controls the display of the outcomes, their ranking and the type of user interaction with possibility of refining the search by some automatic or manual preferences scheme [24].

2.1.1 Color Features for Image Retrieval

Color is widely used low-level visual features and it is invariant to image size and orientation [9].

- Color Histogram: In CBIR, one of the most popular features is the color histogram in HSV color space, which used in MPEG-7 descriptor. At first, the images converted to the HSV color space, and uniformly quantizing H, S, and V components into 16, 2, and 2 regions respectively generates the 64-bit color histogram [44].
- Color moments: To form a 9-dimensional feature vector, the mean μ, standard deviation σ, and skew g are extracted from the R, G, B color spaces. The best known space color and commonly used for visualization is the RGB space color. It can be depict as a cube where the horizontal x-axis as red values increasing to the left, y-axis as blue increasing to the lower right and the vertical z-axis as green increasing towards the top [21].

2.1.2 Texture Feature for Image Retrieval

In the texture feature extraction, using the gray level co-occurrence matrix for the query image and the first image in the database to extract the texture feature vector [19]. The co-occurrence matrix representation is a technique used to give the intensity values and the distribution of the intensities. The features which selected for retrieving texture properties are Energy, Entropy, Inverse difference, Moment of inertia, Mean, Variance, Skewness, Distribution uniformity, Local stationary and Homogeneity [15].

2.1.3 Shape Features for Image Retrieval

The shape defined as the characteristic surface configuration of an object: an outline or contour. The object can be distinguished from its surroundings by its outline [9].

We can divide the shape representations into two categories:

1- Boundary-based shape representation: it uses only the outer boundary of the shape. It works by describing the considered region by using its external characteristics. For example, the pixels along the object boundary [39].
2- Region-based shape representation: it uses the entire shape region. It works by describing the considered region using its internal characteristics. For example, the pixels which the region contained [39].

3 Images in the Neutrosophic Domain with Hesitancy degree

The image in the neutrosophic domain is considered as an array of neutrosophic singletons [25]. Let U be a universe of discourse and W is a set in U which composed of bright pixels. A neutrosophic images

P_{NS} is characterized by three sub sets T, I, and F. which can be defined as T is the degree of membership, I is the degree of indeterminacy, and F is the degree of non-membership. In the image, a pixel P is described as P(T,I,F) which belongs to W by it is t% is true in the bright pixel, i% is the indeterminate and f% is false where t varies in T, i varies in I, and f varies in F. In the image domain, the pixel p(i,j) is transformed to $NDP_{NS}(i,j) = \{T(i,j),\ I(i,j),\ F(i,j)\}$. Where $T(i,j)$ belongs to white set, $I(i,j)$ belongs to indeterminate set and $F(i,j)$ belongs to non-white set.
Which can be defined as [7]:

$$p_{NS}(i,j) = \{T(i,j), I(i,j), F(i,j)$$

$$T(i,j) = \frac{\overline{g(i,j)} - \bar{g}_{\min}}{\bar{g}_{\max} - \bar{g}_{\min}}$$

$$I(i,j) = 1 - \frac{H_0(i,j) - H_0}{H_{0\max} - H_{0\min}}$$

$$F(i,j) = 1 - T(i,j)$$

$$H_0(i,j) = abs(g(i,j) - \overline{g(i,j)}$$

Where $\overline{g(i,j)}$ can be defined as the local mean value of the pixels of window size, and $H_0(i,j)$ can be defined as the homogeneity value of T at (i,j), which described by the absolute value of difference between intensity $\overline{g(i,j)}$ and its local mean value $g(i,j)$.
The second transformation for $NDP_{NS}(i,j) = \{T(i,j),\ I(i,j),\ F(i,j), \pi(i,j)\}$
Where $\pi(i,j) = 3 - T(i,j) - I(i,j) - F(i,j)$ in [25].

4 Texture features in neutrosophic domain

4.1 Neutrosophic Entropy

Shannons Entropy provides an absolute limit on the best possible average length of lossless encoding or compression of an information source.
Generally, you need $log_2(n)$ bits to represent a variable that can take one of n values if n is a power of 2. If these values are equally probable, the entropy is equal to the number of bits equality between number of bits and shannons holds only while all outcomes are equally probable. If one of the events is more probable than others, observations of that event is less informative.
Conversely, rare events provide more information when observed. Since observation of less probable events occurs more rarely, the net effect is that the entropy received from non-uniformly distributed data is than $log_2(n)$. Entropy is zero when one outcome is certain. Shannon entropy quantifies all these considerations exactly quantifies all these considerations exactly when a probability distribution of the source is known. Entropy only takes into account the probability of observing a specific event, so the information which encapsulates is information about the underlying probability distribution, not the meaning of the events themselves [37].
Entropy is defined as [12]:

$$Entropy = \sum_i \sum_j P(i,j) \log(i,j)$$

Although the Neutrosophic Set Entropy was defined in one dimension, presented in [10], we will define it in two dimension to be as follows:

$$EntNS = EnT + EnI + EnF$$

$$EntT = \sum_i \sum_j P_T(i,j) \log P_T(i,j)$$

$$EntI = \sum_i \sum_j P_I(i,j) \log P_I(i,j)$$

$$EntF = \sum_i \sum_j P_F(i,j) \log P_F(i,j)$$

where P contains the histogram counts.
Because, we used the interval between 0 and 1, $logP(i,j)$ may have negative values.
So, we use the absolute of $En_T, En_I, and\ En_F$

4.2 Neutrosophic Contrast

Contrast is the difference in luminance or color that makes an object distinguishable. In visual perception of the real world, contrast is determined by the difference in the color and brightness of the object and other objects within the same field of view. The human visual system is more sensitive to contrast than absolute luminance. The maximum contrast of an image is the contrast ratio or dynamic range. It is the measure of the intensity contrast between a pixel and its neighbor over the whole image, it can be defined as [38]:

$$Contrast = \sum_i \sum_j (i-j)^2 P(i,j)$$

We will define the Neutrosophic set Contrast to be as follows:

$$ContNS = ContT + Cont_I + Cont_F$$

$$Cont_T = \sum_i \sum_j (i-j)^2 P_T(i,j)$$

$$Cont_I = \sum_i \sum_j (i-j)^2 P_I(i,j)$$

$$Cont_F = \sum_i \sum_j (i,j)^2 P_F(i,j)$$

4.3 Neutrosophic Energy

It is the sum of squared elements. Which defined as [13]:

$$Energy = \sum_i \sum_j P^2(i, j)$$

We will define the Neutrosophic set Energy to be as follows:

$$EnNS = EnT + En_I + En_F$$

$$En_T = \sum_i \sum_j P_T^2(i, j)$$

$$En_I = \sum_i \sum_j P_I^2(i, j)$$

$$En_F = \sum_i \sum_j P_F^2 9i, j)$$

4.4 Neutrosophic Homogeneity

Homogeneity describe the properties of a data set, or several datasets. Homogeneity can be studied to several degrees of complexity. For example, considerations of homoscedasticity examine how much the variability of data-values changes throughout a dataset. However, questions of homogeneity apply to all aspects of the statistical distributions, including the location parameter. Homogeneity relates to the validity of the often convenient assumption that the statistical properties of any one part of an overall dataset are the same as any other part. In meta-analysis, which combines the data from several studies, homogeneity measures the difference or similarities between the several studies.
That is a value which measures the closeness of the distribution of elements. Which defined as [20]:

$$Homogeneity = \sum_i \sum_j \frac{p(i, j)}{1 + |i - j|}$$

We will define the Neutrosophic set Homogeneity to be as follows:

$$HomoNS = HomoT + HomoI + Homo_F$$

$$HomoT = \sum_i \sum_j \frac{PT(i, j)}{1 + |i - j|}$$

$$HomoI = \sum_i \sum_j \frac{PI(i, j)}{1 + |i - j|}$$

$$HomoF = \sum_i \sum_j \frac{PF(i, j)}{1 + |i - j|}$$

Recently, the Euclidean distance is calculated between the query image and the first image in the database and stored in an array. This process is repeated for the remaining images in the database followed by storing their values respectively. The array is stored now in ascending order and displayed the first 8 closest matches.

5. Conclusion and Future Work

In this paper, we introduced a survey of the Text-Based Image Retrieval (TBIR) and the Content-Based Image Retrieval (CBIR). We also introduced the image in neutrosophic domain and the texture feature in neutrosophic domain. In the future, we plan to introduce some similarity measurement which may be used to determine the distance between the image under consideration and each image in the database, using the features we introduced in this paper. Hence, the images similar to the image under consideration can be retrieved.

6. References

[1] Albowi S. A., Salama A. A. & Eisa M., New Concepts of Neutrosophic Sets , in International Journal of Mathematics and Computer Applications Research (IJMCAR), 3(4), 95-102, 2013.
[2] Chang N. S. and Fu K. S., A Relational Database System For Images, Pictorial Information Systems, the Series Lecture Notes in Computer Science, 80, 288-321, May 2005.
[3] Chang N. S. and Fu K. S., Query-by Pictorial-Example, IEEE Trans. On Software Engineering SE-, 6(6), 519-524, 1980.
[4] Chang S. K, Pictorial Data-Base Systems, IEEE Computer, 14(11), 13-21, Nov 1981.
[5] Chang S. K, Yan C. W., Dimitroff D. C., and Arndt T., An Intelligent Image Database System, IEEE Trans. Software Eng., 14(5), 681-688, 1988.
[6] Chan Y.K. and Chen C.Y., Image Retrieval System Based on Color Complexity and Color Spatial Features, J. of Systems and Software, 71(1), 65-70, 2004.
[7] Cheng H. D., Guot Y., Zhang Y., A Novel Image Segmentation Approach Based on Neutrosophic Set And Improved Fuzzy C- Means Algorithm, World Scientific Publishing Company, New Math. And Natural Computation, 7(1), 155-171, 2011.
[8] Datta R, Dhiraj, Li J., Wang J. Z., Image Retrieval: Idea, Influences, and Trends of the New Age, ACM Computing Survey, 40(2), 1-60, 2008.
[9] Danish M., Rawat R., Sharma R., A Survey: Content – Based Image Retrieval Based on Color, Texture, Shape & Neuro Fuzzy, Mohd. Danish et al. Int. Journal of Engineering Research and Applications, 3(5), 839-844, Sep-Oct 2013.

[10] Eisa M., A New Approach For Enhancing Image Retrieval Using Neutrosophic Set , International Journal of Computer Applications, 95(8), 0975-8887, June 2014.
[11] Gudivada V. N. and Raghavan J. V., Special Issue on Content-Based Image Retrieval Systems, IEEE Computer Magazine, 28(9), 18-22, 1995.
[12] Gang F. Zh., Li J., BoWu, and Wu Y., Local Patterns Constrained Image Histograms For Image Retrieval, 15 IEEE International Journal Conference on IEEE, 941-944, 2008.
[13] Hearn D. and Baker M. P., Computer Graphics, Englewood Cliffs, NJ: Prentice Hall, ch. 14, 500-504, 1994.
[14] Hanafy I., Salama A.A. and Mahfouz K., Correlation of Neutrosophic Data , in International Refereed Journal of Engineering and Science (IRJES) ,1(2), 39-43, 2012.
[15] Ingle D., Bhatia Sh., Content Based Image Retrieval using Combined Features, International Journal of Computer Applications , 44(17), 0975-8887, April 2012.
[16] Jain R., Guest E., Special Issue on Visual Information Management, Comm. ACM, 40(12), 30-32, Dec. 1997.
[17] Kchang, S. and Hsu, A. Image Information System: Where Do We Go From Here?. IEEE Trans. On Knowledge and Data Engineering, 4(5), 431-442, 1992.
[18] KeKre H. B., Survey of CBIR Techniques and Semantics, International Journal of Engineering Science and Technology (IJEST), 3(5), 4510-4517, May 2011.
[19] Kong F. H., Image Retrieval using Both Color And Texture Features, Department of Information science & Technology, Heilongjiang Proceedings of the Eighth International Conference on Machine learning and Cybernetics, Baoding, 4, 2228-2232, 12-15 July 2009.
[20] Kuijk A. A. M., Advanced in Computer Graphics Hardware III, Springer,1991.
[21] Lee I., Muneesawang P., Guan L., Automatic Relevance Feedback for Distributed Content-Based Image Retrieval, ICGT, IEEE.org FLEX Chip signal processor (MC68175/D), Motorola, 1996.
[22] Narasimhalu A. D., Special Section on Content-Based Retrieval, Multimedia Systems, 3(1), 1-2, 1995.
[23] Pentland A. and Picard R., Special Issue on Digital Libraries, IEEE Trans. Patt. Recog. And Mach. Intell., 18(7- 8), 673-733, 1996.
[24] Saxena K., Richaria V., Trivedi V., A Survey on Content Based Image Retrieval using BDIP, BVLC and DCD, Journal of Global Research in Computer Science, 3(9), 38-41, September 2012.
[25] Salama A. A., Smarandache F. and Eisa M., Introduction to Image Processing via Neutrosophic Techniques, Neutrosophic Sets and Systems, 5, 59-64, 2014.
[26] Salama A. A., Eisa M., Elhafeez S. A., Lotfy M. M., Review of Recommender systems Algorithms Utilized in social Networks based e-Learning Systems & Neutrosophic System, Neutrosophic Sets and Systems, 8, 32- 41, 2015.
[27] Salama A.A., and Elagamy H., Neutrosophic Filters, in International Journal of Computer Science Engineering and Information Technology Reseearch (IJCSEITR), 3(1), 307-312, 2013.
[28] Salama A. A., Basic Structure of Some Classes of Neutrosophic Crisp Nearly Open Sets & Possible Application to GIS Topology, Neutrosophic Sets and Systems, 7, 1-5, 2014.
[29] Salama A. A., Smarandache F., Alblowi S. A., The Characteristic Function of a Neutrosophic Set, Neutrosophic Sets and Systems, 3, 14-17, 2014.
[30] Salama A. A., El-Ghareeb H. A., Manie A. M., Smarandache F., Introduction to Develop Some Software programs for Dealing with Neutrosophic Sets, Neutrosophic Sets and Systems, 3, 51-52, 2014.
[31] Salama A. A., Abdelfattah M., Eisa M., Distances, Hesitancy Degree and Flexible Querying via Neutrosophic Sets, International of Computer Applications, 101(10), 0975-8887, September 2014.
[32] Salama A. A., Eisa M., Abdelmoghny M. M., Neutrosophic Relations Database, International Journal of Information Science and Intelligent System, 3(2), 1-3, 2014.
[33] Salama A. A., Broumi S., Rughness of Neutrosophic Sets, Elixir Appl. Math., 74, 26833-26837, 2014.
[34] Salama A. A., El-Ghareeb H. A., Manie A. M., Lotfy M. M., Utilizing Neutrosophic Set in Social Network Analysis e- Learning Systems, International Journal of Information Science and Intelligent Systems, 3(4), 61-72, 2014.
[35] Salama A. A., Alagamy H., Neutrosophic Filters, International Journal of computer Science Engineering and Information Technology Research, 3(1), 307-312, 2013.
[36] Schatz B. and Chen H., Building Large Scale Digital libraries, Computer, 29(5), 22-26, 1996.
[37] Shannon C. E., A Mathematical Theory of Communication, The Bell System Technical Journal, 27, 379-423, 623-656, Jully, October, 1948.
[38] Sinha M. N., Udai A. D., Computer Graphics, Taha McGraw – Hill publishing company limited.
[39] Sifuzzaman M., Islam M. R. and Ali M. Z., Application of Wavelet Transform and Its Advantage Compared to Fourier Transform, Journal of Physical Sciences, 13, 121-134, 2009.

[40] Smarandache F., Neutrosophic set- A generalization of the Intuitionistic Fuzzy set, Granutar Computing, IEEE International Conference, 38-42, may 2006.
[41] Smarandache F., Neutrosophy and Neutrosophic Logic, First International Conference on Neutrosophy, Neutrosophic Logic, Set, Probability, and Statistics, University of New Mexico, Gallup, USA, 87301, 2002.
[42] Smarandache F., A Unifying Field in Logics: Neutrosophic Logic, Neutrosophy, Neutrosophic Set, Neutrosophic Probability, American Research Press, Rehoboth, NM, 1-41, 1999.
[43] Tamura H. and Yokoya N., Image Database Systems: A Survey, Pattern Recogonition, 17(1), 29-43, 1984.
[44] Toldin P. P., A Survey on Content-Based Image Retrieval / browsing Systems Exploiting Semantic, 9-13, 2010.
[45] Zadeh L.A., Fuzzy sets, Information and Control, 8, 338-353, 1965.

Received: November 30, 2016. Accepted: December 22, 2016