A New Approach in Content-Based Image Retrieval Neutrosophic Domain

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Abstract The aim of this chapter is to present texture features for images embedded in the neutrosophic domain with Hesitancy degree. Hesitancy degree is the fourth component of neutrosophic sets. The goal 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) · Hesitancy degree
Text-based image retrieval (TBIR) · Neutrosophic domain
Neutrosophic entropy · Neutrosophic contrast · Neutrosophic energy
Neutrosophic homogeneity

1 Introduction

With an explosive growth of digital image collections, content based image retrieval (CBIR) has been emerged as one of the most active problems in computer vision as well as multimedia applications. The target of content-based image retrieval (CBIR) [3] is to retrieve images relevant to a query of a user, which can be expressed by

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example. In CBIR, an image is described by automatically extracted low-level visual features, such as color, texture and shape [11, 16, 18]. When a user submits one or more query images as examples, a criterion based on this image description ranks the images of an image database according to their similarity with the examples of the query and, finally, the most similar are returned to the Digital image retrieval systems. Since 1990s, Content Based Image Retrieval (CBIR) has attracted great research attention [12, 37]. Early research was focused on finding the best representation for image features. The current work primarily focuses on using Neutrosophic sets with Hesitancy degree Transformation methods for CBIR.

The Neutrosophic logic which was proposed by Smarandache in [33] is a generalization of fuzzy sets which introduced by Zadeh at 1965 [38]. The fundamental concepts of neutrosophic sets were introduced by Smarandache in [34, 35] and Salama et al. in [1, 8, 20–29]. We will now extend the concepts of distances to the case of neutrosophic hesitancy degree by taking into account the four parameters characterization of neutrosophic sets [19].

2 Image Retrieval Techniques

2.1 Content-Based Image Retrieval (CBIR)

Content Based Image Retrieval is one of the important methods for image retrieval system. It enhances the accuracy of the image being retrieved, It is applicable for efficient query processing, automatically extract the low-level features such as texture, intensity, shape and color in order to classify the query and retrieve the similar images from the huge scale image collection of database. In CBIR, each image that is stored in the database has its features extracted and compared to the query image features [17]. Eakins [9] has divided image features into three levels:

Level 1—This level deals with primitive features like color, texture, shape or some spatial information about the objects in the picture. This way we can filter images on a more global scale based on form or color. This can be used for finding images that are visually similar to the query image.

Level 2—This level introduces the logical features or derived attributes which involve some degree of inference about the identity of the objects depicted in the image. So a typical query in a medical scope would be "Find images of a kidney".

Level 3—Most complex of all levels, as it requires complex reasoning about the significance of the objects depicted. In this case the query would look like "Find image of an infected kidney".

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 [4].

- 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 [36].
- 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 [15].

2.1.2 Texture Feature for Image Retrieval

The gray level co-occurrence matrix for the query image and the first image in the database is used to extract the texture feature vector [13]. The co-occurrence matrix representation is a technique used to give the intensity values and the distribution of the intensities. The features which are selected for retrieving texture properties are Energy, Entropy, Inverse difference, Moment of inertia, Mean, Variance, Skewness, Distribution uniformity, Local stationary and Homogeneity [10].

2.1.3 Shape Features for Image Retrieval

A shape is defined as the characteristics surface configuration of an object: an outline or contour. An object can be distinguished from its surroundings by its outline [4].

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 [32].
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 [32].

3 Hesitancy Degree

We will now extend the concepts of distances to the case of neutrosophic hesitancy degree. By taking into account the four parameters characterization of neutrosophic sets $A = \{\langle \mu_A(x), \upsilon_A(x), \gamma_A(x), \pi_A(x)\rangle, x \in X\}$ [19].

Definition 3.1 [19] Let $A = \{(\mu_A(x), \upsilon_A(x), \gamma_A(x)), x \in X\}$ and $B = \{(\mu_B(x), \upsilon_B(x), \gamma_B(x)), x \in X\}$ on $X = \{x_1, x_2, x_3, \ldots, x_n\}$.

For a Neutrosophic set $A = \{(\mu_A(x), \upsilon_A(x), \gamma_A(x)), x \in X\}$ in X, We call $\pi_A(x) = 3 - \mu_A(x) - \upsilon_A(x) - \gamma_a(x)$, the Neutrosophic index of x in A, It is a hesitancy degree of x to A it is obvious that $0 \le \pi_A(x) \le 3$.

4 Images in the Neutrosophic Domain with Hesitancy Degree

The image in the neutrosophic domain is considered as an array of neutrosophic singletons [19]. 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 its t% is truthness in the bright pixel, i% is the indeterminacy and f% is the falsity 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 indeterminacy set and $F(i, j)$ belongs to non-white set which can be defined as in [2]:

$$P_{NS}(i, j) = \{T(i, j), I(i, j), F(i, j)\} \tag{1}$$

$$T(i, j) = \frac{\overline{g(i, j)} - \bar{g}_{min}}{\bar{g}_{max} - \bar{g}_{min}} \tag{2}$$

$$I(i, j) = 1 - \frac{H_0(i, j) - H_0}{H_{0_{max}} - H_{0_{min}}} \tag{3}$$

$$F(i, j) = 1 - T(i, j) \tag{4}$$

$$\pi(i, j) = 3 - T(i, j) - I(i, j) - F(i, j) \tag{5}$$

$$H_0(i, j) = abs\left(g(i, j) - \overline{g(i, j)}\right) \tag{6}$$

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 $g(i, j)$ and its local mean value $\overline{g(i, j)}$.

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 [19].

5 Texture Features in Neutrosophic Domain

5.1 Neutrosophic Entropy with Hesitancy Degree

Shannons Entropy provides an absolute limit on the best possible average length of lossless encoding or compression of an information source.

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 then $\log_2(n)$. Entropy is zero when one outcome is certain. Shannon entropy 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 [30]. Entropy is defined in [6]:

$$Entropy = \sum_i \sum_j P(i, j)\log P(i, j) \tag{7}$$

Although, the neutrosophic set entropy was defined in one dimension which presented in [5], we will define it in two dimensions to be as follows:

$$En_{Ns} = En_T + En_I + En_F \tag{8}$$

$$En_T = \sum_i \sum_j P_T(i, j)\log P_T i, j \tag{9}$$

$$En_I = \sum_i \sum_j P_I(i, j)\log P_I(i, j) \tag{10}$$

$$En_F = \sum_i \sum_j P_F(i, j)\log P_F(i, j) \tag{11}$$

$$En_\pi = 3 - (En_T + En_I + En_F) \tag{12}$$

where P contains the histogram counts.

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

5.2 Neutrosophic Contrast with Hesitancy Degree

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 in [31]:

$$Contrast = \sum_i \sum_j (i-j)^2 P(i,j) \tag{13}$$

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

$$contrast_{NS} = contrast_T + contrast_I + contrast_F \tag{14}$$

$$contrast_T = \sum_i \sum_j (i-j)^2 P_T(i,j) \tag{15}$$

$$contrast_I = \sum_i \sum_j (i-j)^2 P_I(i,j) \tag{16}$$

$$contrast_F = \sum_i \sum_j (i-j)^2 P_F(i,j) \tag{17}$$

$$contrast_\pi = 3 - (contrast_T + contrast_I + contrast_F) \tag{18}$$

5.3 Neutrosophic Energy with Hesitancy Degree

It is the sum of squared elements which is defined in [7]:

$$Energy = \sum_i \sum_j P^2(i,j) \tag{19}$$

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

$$Energy_{NS} = Energy_T + Energy_I + Energy_F \tag{20}$$

$$Energy_T = \sum_i \sum_j P_T^2(i,j) \tag{21}$$

$$Energy_I = \sum_i \sum_j P_I^2(i,j) \tag{22}$$

$$Energy_F = \sum_i \sum_j P_F^2(i,j) \tag{23}$$

$$Energy_{\pi} = 3 - (Energy_T + Energy_I + Energy_F) \tag{24}$$

5.4 Neutrosophic Homogeneity with Hesitancy Degree

Homogeneity describes 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 is defined in [14]:

$$\text{Homogeneity} = \sum_i \sum_j \frac{P(i, j)}{1 + |i - j|} \tag{25}$$

We will define the neutrosophic set homogeneity to be as follows:

$$\text{Homogeneity}_{NS} = \text{Homogeneity}_T + \text{Homogeneity}_I + \text{Homogeneity}_F \tag{26}$$

$$\text{Homogeneity}_T = \sum_i \sum_j \frac{P_T(i, j)}{1 + |i - j|} \tag{27}$$

$$\text{Homogeneity}_I = \sum_i \sum_j \frac{P_I(i, j)}{1 + |i - j|} \tag{28}$$

$$\text{Homogeneity}_F = \sum_i \sum_j \frac{P_F(i, j)}{1 + |i - j|} \tag{29}$$

$$\text{Homogeneity}_{\pi} = 3 - (\text{Homogeneity}_T + \text{Homogeneity}_I + \text{Homogeneity}_F) \tag{30}$$

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.

6 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 with hesitancy degree and the texture feature in neutrosophic domain. In 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 have introduced in this chapter. Hence, the images similar to the image under consideration can be retrieved.

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