Content-based Image Retrieval with Color and Texture Features in Neutrosophic Domain

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***Abstract*—In this paper, a new content-based image retrieval (CBIR) scheme is proposed in neutrosophic (NS) domain. For this task, RGB images are first transformed to three subsets in NS domain and then segmented. For each segment of an image, color features including dominant color discribtor (DCD), histogram and statistic components are extracted. Wavelet features are also extracted as texture features from the whole image. All extracted features from either segmented image or the whole image are combined to create a feature vector. Feature vectors are presented for ant colony optimization (ACO) feature selection which selects the most relevant features. Selected features are used for final retrieval process. Proposed CBIR scheme is evaluated on Corel image dataset. Experimental results show that the proposed method outperforms our prior method (with the same feature vector and feature selection method) by 2% and 1% with respect to precision and recall, respectively. Also, the proposed method achieves the improvement of 13% and 2% in precision and recall, respectively, in comparison with prior methods.**

***Index Terms*—Content-based image retrieval, neutrosophic domain, ant colony optimization, color features, texture features.**

I. Introduction

Content-based image retrieval (CBIR) is a task of retrieving relevant images from a presented query image based on visual characteristics. It is more useful than retrieving images based on text describers which were created by human. Each image in database is mapped to a feature vector including visual, structural and conceptual characteristics. Similarity between the feature vector of the query image and the images in database is used to retrieve relevant images [1]. The main contributions of the prior CBIR systems are related to feature extraction methods and similarity measures. Color and texture features are among low-level features which are extensively used in CBIR [2]. The color is widely used in CBIR systems since its extraction is usually easy as well as its performance is relatively high for retrieving task. Texture features are extracted and described from statistical, structural, and spectrum methods. Many CBIR systems have been proposed based on color and texture features [1]–[7].

Feature selection is a method that finds the most relevant features among a feature vector. Many feature selection approaches have been proposed for different applications such as face recognition [8], data mining and pattern recognition [9], automatic speaker verification [10] and so on. Ant colony optimization (ACO) has been applied for feature selection task [11]–[13]. Feature selection has also been applied for CBIR systems [4], [14], [15].

Neutrosophy (NS) is a branch of philosophy which studies the nature and scope of the neutralities and their interactions which is the basis of neutrosophic logic and neutrosophic (NS) set [16]. This theory was applied for image processing first by Guo et al. [17] and it has subsequently been successfully used for other image processing operations including image segmentation [17]–[20], image thresholding [21], medical image segmentation [22] and edge detection [23]. Also, NS has been adapted for data and image clustering as well [24].

This paper extends our previous work in [4] which was based on color and texture features followed by ACO feature selection. In this work, the same features are used as well as the same feature selection method. The main contributions of this paper are as follows: first RGB images in pixel domain are transformed to 3 subsets T_R, T_G and T_B in NS domain to make T_{RGB}. Then, transformed images to NS domain are segmented and features are extracted from each segment separately. This idea improves the retrieval performance for image classes which are characterized by specific objects. It may be noted that this work is the first approach to make use of NS logic for CBIR application.

The rest of this paper is organized as follows: Section II describes the neutrosophic set. Proposed method is presented in Section III. Experimental setup and results are described in Sections IV. Discussion is presented in Section V. Finally, the conclusion and future works are discussed in Section VI.

II. Neutrosophic set

Consider that X is a universal set in the NS domain and a set A is included in X. Each member x in A is described with three real subsets of $[0, 1]$ named as T, I and F. Element x in set A is expressed as $x(t, z, f)$, where t, z and f vary in T, I and F, respectively. $x(t, z, f)$ could be interpreted as it is t% true, z% indeterminate, and f% false that x belongs to A. T, I and F could be considered as membership sets [16].

Consider an image g with L gray levels. g can be mapped into T , I and F sets. Thus, the pixel $p(i, j)$ in g is transformed

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into $PNS(i,j) = T(i,j), I(i,j), F(i,j))$ or $PNS(t,z,f)$ in neutrosophic domain. T, I and F are considered as white, noise and black pixel sets, respectively. $PNS(t,z,f)$ means that this pixel is $\%t$ true to be a white pixel, $\%z$ to be a noisy pixel and $\%f$ to be a black pixel. T, I and F are computed as follows [17], [25]:

$$T(i,j) = \frac{\overline{g(i,j)} - \overline{g_{min}}}{\overline{g_{max}} - \overline{g_{min}}} \tag{1}$$

$$F(i,j) = 1 - T(i,j); \tag{2}$$

$$I(i,j) = \frac{\delta(i,j) - \delta_{min}}{\delta_{max} - \delta_{min}}; \tag{3}$$

$$\overline{g(i,j)} = \frac{1}{w^2} \sum_{m=-\frac{w}{2}}^{\frac{w}{2}} \sum_{n=-\frac{w}{2}}^{\frac{w}{2}} g(i+m, j+n) \tag{4}$$

$$\delta(i,j) = |g(i,j) - \overline{g(i,j)}| \tag{5}$$

where g is the gray scale image, $\overline{g}$ is a filtered version of the image g filtered with an averaging filter, w is the window size for the averaging filter, $\overline{g_{max}}$ and $\overline{g_{min}}$ are the maximum and minimum of the $\overline{g}$, respectively, δ is the absolute difference between g and $\overline{g}$, δ_{max} and δ_{min} are also the maximum and minimum values of δ, respectively [17].

III. Proposed method

A. Image segmentation in NS domain

In CBIR systems, each image is mapped to a feature vector. The feature vector of query images are compared with the feature vector of images in dataset and then the relevant images are retrieved. In conventional feature extraction methods, features are extracted from the whole image in pixel domain while in this work, features are extracted from each segment of an image in NS domain. For this task, Algorithm 1 is proposed in which R, G and B components of images are first transformed to T_R, T_G, T_B, I_R, I_G and I_B in NS domain. Note that subset F is not used here since it does not have any role in retrieval process. Then, α-mean and β-enhancement operations, proposed in [17], are applied to T_R, T_G, T_B, I_R, I_G and I_B subsets repeatedly until there is no significant change in the entropy of the subset I. The indeterminacy set I has important role for decreasing the effect of noise. In this application, there are 3 indeterminacy sets I_R, I_G and I_B. All these sets are assigned to the $max(I_R, I_G, I_B)$. This idea ensures that in each component, pixels with bigger indeterminacy are more penalized by a filter to decrease the noise effect. The indeterminacy of a pixel in each component is different. Therefore, we considered the maximum indeterminacy to have the maximum penalty for noisy pixels. After that, T_R, T_G are T_B combined to create T_{RGB} in NS domain and then k-mean clustering is applied to segment T_{RGB}.

Algorithm 1 Proposed image segmentation in NS domain.

1: Inputs: g (input image in RGB domain), Output: Segmented T_{RGB} in NS domain.

2: Transfer g_R, g_G and g_B in pixel domain to T_R, T_G, T_B, I_R, I_G and I_B in NS domain. Each component is transformed separately by (1)-(13).

3: Consider a rectangular Gaussian filter h with the dimension of $[3,3]$.

4: Apply α-mean operation to T_R, T_G, T_B I_R, I_G and I_B set as follows:

$$\bar{T}(\alpha) = \begin{cases} T(i,j), & \text{if } I(i,j) < \alpha \\ \bar{T}_\alpha(i,j), & \text{otherwise} \end{cases} \tag{6}$$

$$\bar{T}_\alpha(i,j) = \frac{1}{w^2} \sum_{m=-\frac{w}{2}}^{\frac{w}{2}} \sum_{n=-\frac{w}{2}}^{\frac{w}{2}} T(i+m, j+n) \tag{7}$$

$$\bar{I}_\alpha(i,j) = \frac{\bar{\delta}_T(i,j) - \bar{\delta}_{Tmin}}{\bar{\delta}_{Tmax} - \bar{\delta}_{Tmin}} \tag{8}$$

$$\bar{\delta}_T(i,j) = |\bar{T}(i,j) - \bar{\bar{T}}(i,j)| \tag{9}$$

$$\bar{\bar{T}}(i,j) = \frac{1}{w^2} \sum_{m=-\frac{w}{2}}^{\frac{w}{2}} \sum_{n=-\frac{w}{2}}^{\frac{w}{2}} \bar{T}(i+m, j+n) \tag{10}$$

5: Apply β-enhancement operation to T_R, T_G, T_B I_R, I_G and I_B set as follows:

$$T'(\beta) = \begin{cases} T(i,j), & \text{if } I(i,j) < \alpha \\ {T'}_\beta(i,j), & \text{otherwise} \end{cases} \tag{11}$$

$${T'}_\beta(i,j) = \begin{cases} 2T^2(i,j), & \text{if } T(i,j) <= 0.5 \\ 1 - 2(1 - T(i,j))^2, & \text{otherwise} \end{cases} \tag{12}$$

$${I'}_\beta(i,j) = \frac{\delta'_T(i,j) - {\delta'}_{Tmin}}{{\delta'}_{Tmax} - {\delta'}_{Tmin}} \tag{13}$$

$$\delta'_T(i,j) = |T'(i,j) - \bar{T}'(i,j)| \tag{14}$$

$$\bar{T}'(i,j) = \frac{1}{w^2} \sum_{m=-\frac{w}{2}}^{\frac{w}{2}} \sum_{n=-\frac{w}{2}}^{\frac{w}{2}} T'(i+m, j+n) \tag{15}$$

6: Set I_R, I_G and I_B to $max(I_R, I_G, I_B)$.

7: If $|Entropy(I_R^t) - Entropy(I_R^{t-1})| < 0.001$ go to 8, otherwise go to 4.

8: Combine T_R, T_G, T_B to create color image T_{RGB} in NS domain.

9: Apply k-mean clustering to T_{RGB}.

10: Return segmented image in NS domain in which each cluster is a segment.

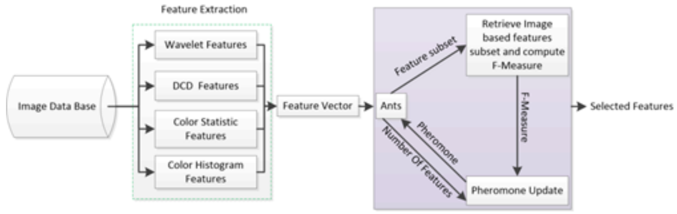

Fig. 1: Selection of the most relevant features among extracted color and texture features by ACO [4].

B. Feature extraction and selection

In this work, proposed color and texture features in our previous work [4] are used for feature extraction. For Color features, three type of features including DCD, color statistic and color histogram features are extracted. In DCD, both representative colors and the percentage of each color are included. Moreover, DCD provide an effective and compact color representation, could be applied for color distribution in an image or a region of interest [3]. Here, the DCD features are extracted in RGB domain. Each pixel value is replaced by the center of its corresponding partition. As a result, by applying DCD to an image, quantized image is achieved which the number of colors for that image is equal with the number of partitions. As the simplest statistic features, the first order (mean, denoted my M) and the second order (standard deviation, denoted by STD) are color statistics features. For each color channel such as R, G and B, a color histogram graph is drawed with respect to bin size B (the number of intervals or range resolutions). Each color channel has B histogram features correspond to the number of pixels dropped to each interval.

For texture features, wavelet features are extracted based on the wavelet transformation using approximation, vertical and horizontal frequency components of an image. The decomposed image by Haar filter consists of LL, LH, HL and HH components in each level. LL includes low frequency factors and HL, LH and HH include factors of high frequencies in horizontal, vertical and diagonal directions, respectively. The norm of the rows of LL and LH matrices and the norm of the columns of HL matrix are computed as wavelet features.

Images are transformed to NS domain and segmented to 5 segments ($K = 5$) by Algorithm 1. DCD, color statistic features and color histogram features are extracted from all 15 segments in NS domain. Note that each image is transformed to 3 sets T_R, R_G, and T_B in NS domain and each set is segmented to 5 segments. Finally, wavelet features are extracted from the whole T_R, R_G, and T_B components.

Extracted features are presented for feature selection method which is proposed in our previous work [4]. This method is based on ACO which is an iterative, probabilistic metaheuristic method for the solution of hard combinatorial optimization problems [26]. As it is shown in Fig. 1, the most relevant features are selected among extracted color and texture features.

C. Similarity measure

The similarity between extracted features from query image and the images in database is considered as a measure to retrieve images. Selected features by ACO is categorized based on feature types. Euclidean distance is used as similarity measure for wavelet and color statistic features. Finally, similarity measures in [3], [27] are used for color histogram features and wavelet features, respectively.

IV. Experimetnal setup and results

In each experiment, an image is presented as query and then relevant images are retrieved. Before feature extraction, all images are transformed to NS domain and then segmented by Algorithm 1. Fig. 2 shows the segmented images in NS domain for 10 sample images. For simplicity, all images are resized to 256x256 pixels. The number of dominant colors in DCD feature extraction is 8. Each image is segmented to 5 segments in NS domain. Therefore, for T_R, T_G and T_B subsets 120 DCD features are extracted. Furthermore, 30 features are extracted as standard deviation and mean of 15 segments in all 3 subsets in NS domain. For histogram features, we set the bin number to 8. Therefore, for all segments of NS components, 120 features are extracted as histogram features.

Texture features are extracted from images in NS domain, not from segmented images. Since the images are in the size of 256x256, the wavelet decompositions LL, LH and HL are all 128x128. The norm of each row in LL and LH and the norm of each column in HL are all the vector of size 1x128. So, for each color component in NS, we have 3 features as standard deviation and 3 features as mean of these three vectors which leads to 18 texture features. After feature extraction, a 258-dimension feature vector is extracted from each image. ACO feature selection method selects 84 relevant features among the extracted features for final retrieval procedure. Our proposed method is evaluated on Corel image database which have been widely used by the image processing and CBIR research communities that consists of 11,000 images of 110 categories including bus, horse, flower, dinosaur, building, elephant, people, beach, scenery and dish. To evaluate the performance of the proposed CBIR method, it has been compared with proposed CBIR systems in [3], [4], [7], [28]. From Corel database, all images have been used as query images and then the first 20 most similar images are retrieved. For each class of image, both average precision and recall are computed for all 100 query images in each class. Results for all image categories are reported in Table I. With respect to preciion measure, the proposed method with 65%, outperform methods in [3], [4], [7], [28] with 53%, 53%, 58% and 63%, respectively.

The retrieved results for a sample query image from CBIR systems in [3], [4], [7], [28] and the proposed CBIR system are shown in Figs 3-7, respectively.

V. Discussion

One of the benefits of the proposed method is that features are extracted from image segments instead of the whole image.

TABLE I: Average precision and recall for the proposed CBIR system and prior systems.

Image Category	Proposed Method		Method in [4]		Method in [7]		Method in [28]		Method in [3]	
	Precision	Recall	Precision	Recall	Precision	Recall	Precision	Recall	Precision	Recall
African people	0.489	0.0978	0.448	0.089	0.453	0.115	0.424	0.126	0.522	0.104
Beach	0.483	0.0966	0.472	0.094	0.398	0.121	0.446	0.113	0.462	0.092
Building	0.624	0.1248	0.534	0.106	0.374	0.127	0.411	0.132	0.444	0.088
Buses	0.713	0.1426	0.734	0.146	0.741	0.092	0.852	0.099	0.558	0.111
Dinosaurs	1	0.2	0.998	0.199	0.915	0.072	0.587	0.104	0.892	0.178
Elephants	0.593	0.1186	0.568	0.113	0.304	0.132	0.426	0.119	0.442	0.088
Flowers	0.912	0.1824	0.875	0.175	0.852	0.087	0.898	0.093	0.863	0.172
Horses	0.713	0.1426	0.707	0.141	0.568	0.102	0.589	0.103	0.601	0.12
Mountains	0.464	0.0928	0.393	0.078	0.293	0.135	0.268	0.152	0.446	0.089
Food	0.604	0.1208	0.61	0.123	0.369	0.129	0.427	0.122	0.619	0.123
Average	**0.6595**	**0.1319**	**0.633**	**0.126**	**0.527**	**0.111**	**0.533**	**0.116**	**0.5849**	**0.1165**

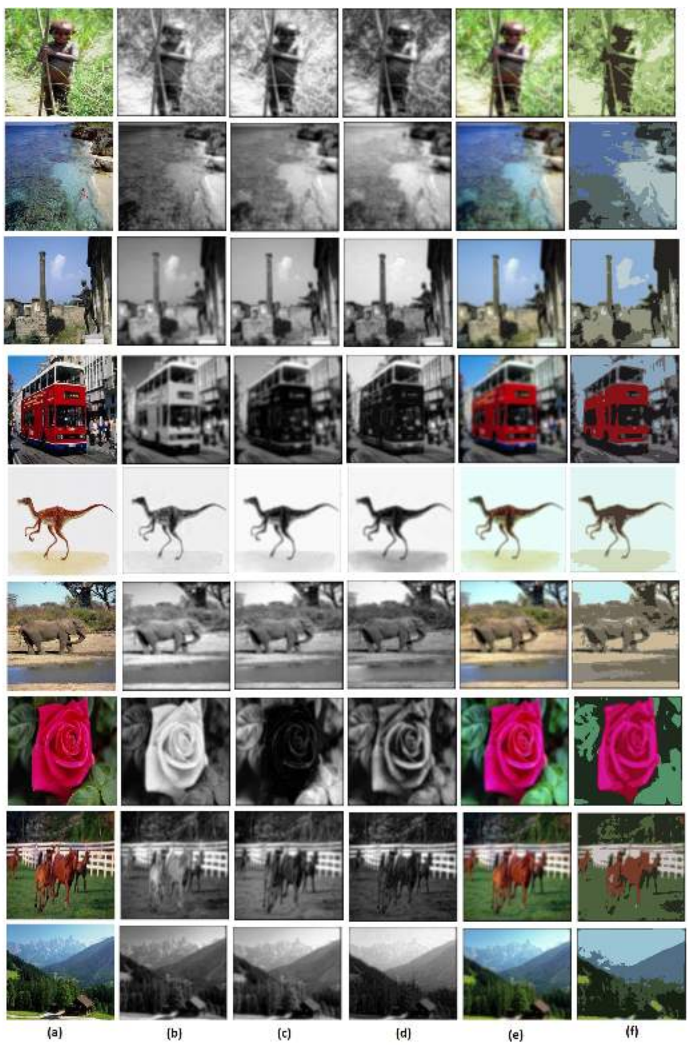

Fig. 2: 10 samples of segmented images in NS domain: (a) input image, (b) T_R, (c) T_G, (d) T_B, (e) T_{RGB} and (f) segmented image.

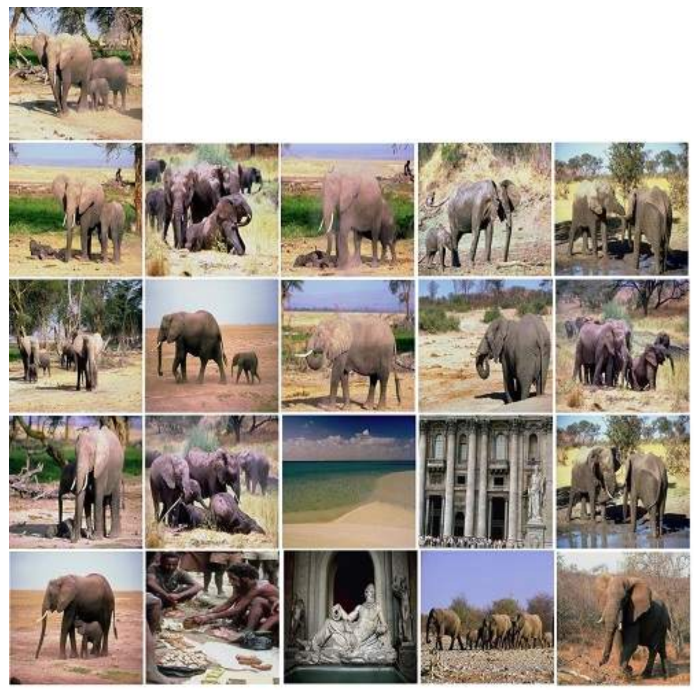

Fig. 3: Retrived images for CBIR system in [7].

It can be useful for image categories which are characterized with specific objects. To have a fair comparison and show that how segmentation process improves the retrieval results, the proposed idea has been compared with [4] with the same feature extraction and selection procedures. Form reported results in Table I, it can be concluded that in some categories containing specific objects, proposed idea improved the retrieval results. For example, in African people, mountain, building, elephant and flower categories, there are 4%, 7%, 9%, 3% and 4% improvement with respect to precision, respectively. In categories with different type of objects such as food category, the precision is decreased.

Determining the number of segments (K) is one of the main challenges. If it is selected small, more general segments are created and the extracted features is almost same with the extracted features from the whole image. On the other hand, if K is selected with bigger values, more specific clusters are selected. Our experiments show that $K = 5$ is the best trade of which leads to better retrieval results in all categories.

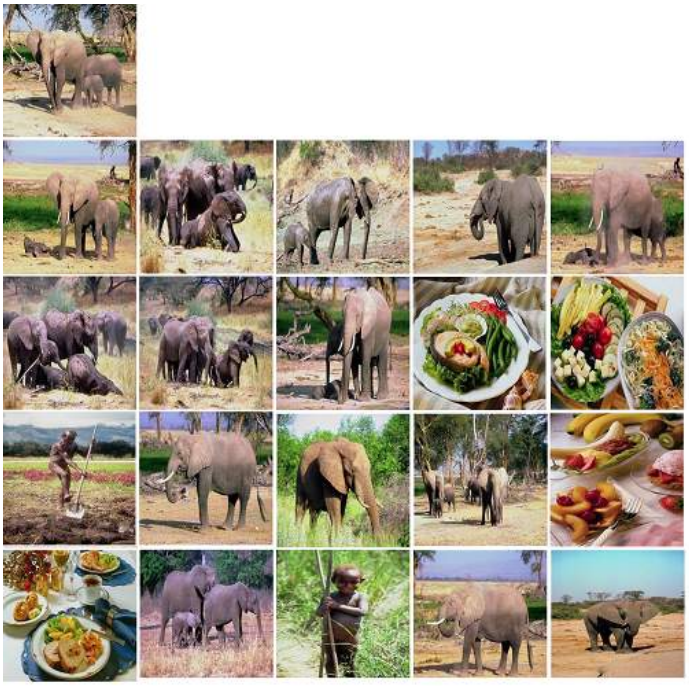

Fig. 4: Retrived images for CBIR system in [28].

Fig. 6: Retrived images for CBIR system in [4].

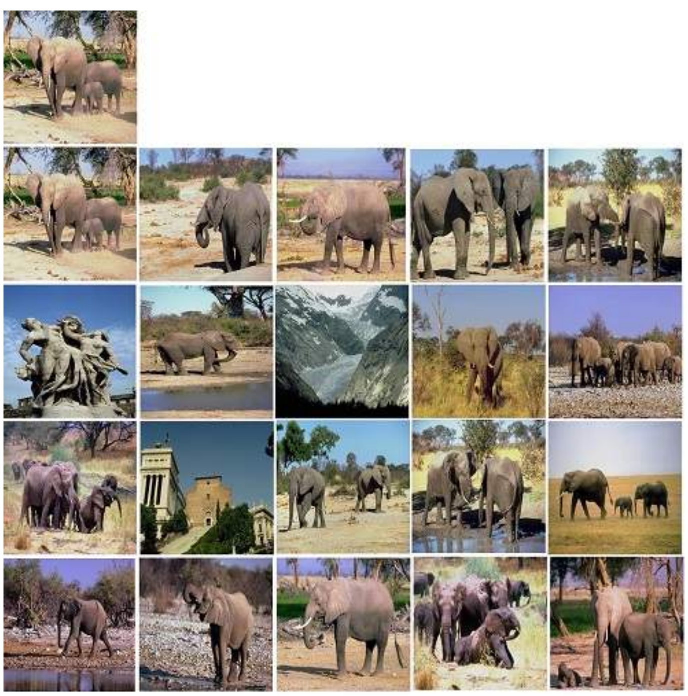

Fig. 5: Retrived images for CBIR system in [3].

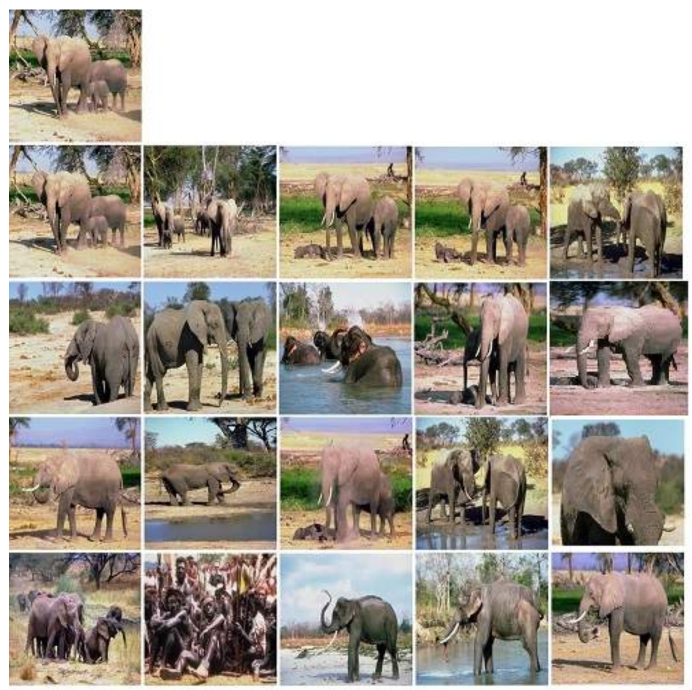

Fig. 7: Retrived images for the proposed CBIR system.

VI. Conclusion and future works

This paper presented a CBIR scheme in NS domain. In the proposed idea, images are transformed and then segmented in NS domain. For each image in NS domain, color feature vector is extracted from the segmented image while texture feature vector is extracted from the whole image. Extracted features are presented for ACO feature selection to select the most relevant features to be used for retrieval process. Experimental results showed that the proposed scheme achieves better retrieval results in comparison with prior works. Future efforts will be directed towards weighting segmented objects in NS domain to assign bigger weights to specific objects which characterize image categories. Future efforts will also be directed towards fine-tuning the number of clusters adaptively.

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