International Journal of Sciences: Basic and Applied Research (IJSBAR)

ISSN 2307-4531
(Print & Online)

http://gssrr.org/index.php?journal=JournalOfBasicAndApplied

Content-Based Image Retrieval Hybrid Approach using Artificial Bee Colony and K-means Algorithms

Abbas F. H. Alharan[a]*, Ali S. A. Al-Haboobi[b], Hasan T. R. Kurmasha[c], Azal J. M. Albayati[d]

[a,b]*Faculty of Education for Girls, Computer Department, University of Kufa, Najaf 31001, Iraq*
[c]*Faculty of Computer Science and Mathematics, Computer Department, University of Kufa, Najaf 31001, Iraq*
[d]*Scientific Division, Youth and Sport Forums of Babylon, 51001 Hillah, Babylon, Iraq*
[a]*Email: abbasf.abood@uokufa.edu.iq*
[b]*Email: ali.alhaboobi@uokufa.edu.iq*
[c]*Email: hasant.kurmasha@uokufa.edu.iq*

Abstract

In this paper, a new clustering method is proposed for CBIR system; this method depends on combining ABC and k-means algorithm. Four features are used with the proposed method to retrieve the images. These features are extracted by: color histogram of HSV image and color histogram of opponent image to describe the color, Gabor filters and Ranklet transform for RGB image to describe the texture. The proposed hybrid clustering method is a clustering process for database of each feature using k-means algorithm enhanced by ABC algorithm. The innovation in this approach is that each solution in ABC algorithm represents the centroids of clusters that come out from applying k-means algorithm. The proposed method is applied on Wang dataset (1000 images in 10 classes) and evaluated by comparing the test results of the proposed scheme with another existing method uses same database. The results proved that the proposed method is superior to the existing method in terms of the precision in 6 out of 10 categories of WANG dataset, such that the average of the precisions for all categories is 0.8093.

----

* Corresponding author.

Keywords: Contents-based image retrieval; CBIR; Feature Extraction; Clustering; Artificial bee colony; K-means clustering algorithm.

1. Introduction

Nowadays, daily storage centers of many businesses such as the military, civilian, medical and internet collect huge amount of digital images archive. Contrary to the case of simple data of images, the dealing with massive data of images will be failing without effective management (browsing, searching and retrieval). For that, the exponentially growing amount of image data raises a big challenge in the area of image retrieval system especially with varied collection of images. The image retrieval is a method to searching for images in large database of images. Out of the prior studies, the image retrieval field is adopting two approaches; they are text-based image retrieval and content-based image retrieval [34, 47, 43]. Formerly, the text-based image retrieval (TBIR) method was the traditional way of handling sets of image database. The framework of TBIR depends mainly on using the textual annotation to describe the images. Although the text-explicit method is easy and simple to apply, it requires non-repetitive and large number of keywords to describe image with many features, thus more time and effort of labor are consumed. These flaws have made the traditional way incompetent and inefficient to yielding accurate description for the image contents [9].

Today, content-based image retrieval (CBIR) methods are used to overcome the existing problems in the TBIR approach. In CBIR, the indexing and retrieval of images rely on the visual contents. Visual content of images is collection of low level features that can be extracted and used to describe the texture, color, and shape features of an entire image. since discovering the CBIR concept until now a lot of researches have been written to develop the CBIR approach but there are some problems that need to solve. The first is obtaining the good features by using the suitable describing method. The second is the dealing with features of huge database images. For that, we will propose a method to tackles the previous problems, the proposed method based on clustering technique using artificial bee colony and k-means algorithms.

Clustering technique (cluster analysis) is one of the most widely used techniques for unsupervised classification. It is a commonly applied in many applications such as data mining, image segmentation, pattern recognition, data analysis and machine learning. Clustering is the process of converting a set of objects (data) into groups of objects. The principle of clustering is the detection of the similarities (distance, time and so on) between data objects, such that each group or cluster with the most similarity is considered as an object [14]. The main goal of image features clustering in image retrieval is to decrease the search space between images and the query image by comparing the query image with the center of the cluster. The retrieved images are the images that belong to the best cluster. K-means is one of the most popular partitioning clustering methods proposed by Stuart Lloyd firstly in 1957. It is a method used in analyzing data into predefined number of clusters. Although k-means is simple and easy to understand and faster in obtaining the optimal local solution, it does not has guarantee to get the optimum solution because it relies on selected centroids as its initial partition [1, 4]. The integration of ABC with the k-means algorithm aims to address the optimal solution problem for the clustering. The ABC algorithm was proposed by Karaboga as a simulation of real bee colony behavior in foraging [20]. The wide acceptance and popularity of ABC due that it is easy to implement, simple and has few control parameters [42]. As at today, many applications utilize the ABC algorithm in their work. The ABC algorithm can also be used as a measure for the compactness and separation of clusters using the objective function.

The rest of the paper is structured as follows: Section two reviews related literature in the study domain; Section three presents the proposed system adopted by this study; Section four discusses the results of the study; and Section five concludes the study.

2. Related works

The proliferation in the advancement of digital technologies such as photographic devices and its varied use in trading, satellite, medicine, social media, etc. has led to the increase in volume of different types of images [50]. This has also led to difficulties in managing massive databases of digital images thereby posing different challenges and obstacles to users when searching across these large databases and discriminating among a huge number of images [19]. Because of these difficulties, it has become necessary to have the so-called automatic image retrieval. Image retrieval can be defined as a computer system employed for searching and retrieving specific number of images from database of images. The TBIR systems have witnessed several progresses such as multi-dimensional indexing, query assessment and image data forming [45]. The first actual TBIR system was presented by Prasad *and his colleagues* in [31]; this system is based on textual and numeric information. From 1987 until 1991, many attempts have been made to develop TBIR systems but were not feasible since the TBIR method primarily relies on manual labeling for images. TBIR method cannot provide robust and obvious description for images.

Accordingly, the content-based image retrieval (CBIR) method is proposed to address the setback of TBIR approach [41]. CBIR is unlike TBIR method, it uses an image as input (query) to search in database of images and retrieve specific number of images that most similar to the image query. In CBIR, the comparison between the image query and the images in database made on the basis of their visual contents. There are several CBIR systems have been developed for the general purpose such as QBIC [12] and Virage [4] are examples for commercial systems. As well as, the academic systems such as CORE [44] and PhotoBook [30]. Also there are other systems such as VisualSeek [38], NeTra [26], IRIS [2].

The first attempt to developing the image visualization was by the authors in [40]. They proposed a method called image histogram that relied on the color of the object to index the image. This method represents the color distribution in the image, where each bin in the histogram represents a color and its amount. Another study in [47] focused on the use of image color extraction for image retrieval. This method employs the color histogram and color moment to describe the image for better retrieval accuracy. In addition, it divides the image into three regions (horizontally, equal and overlapping) to minimize the magnitude of color information used for indexing the color moments. As stated in [15, 18], color-based image retrieval is more effective and quicker in identifying the color distributive features for images in the case of the simple requirements. In another related work by BENČO and Hudec [6], the authors proposed a new method to describe the texture by improving the GLCM method. The new method called color GLCM or CGLCM; it exploited the color information using GLCM for better retrieval. An image retrieval method based on Gabor filter had been proposed in [48]. Rotation normalization is realized by a circular shift of the feature elements so that all images have the same dominant direction. Huang *and his colleagues* in [15] presented a content based image retrieval method that is based on two features (color and texture). In their method, they used the color moment for color feature extraction, and the Gabor filter for texture feature extraction. Duan and his colleagues in [10] combined three features (color, texture and shape) to increase the accuracy of image retrieval in CBIR application. Their proposed method denotes the advantages of CBIR by combining more than one feature and comparing with individual features. In [33], the authors proposed the Features from Accelerated Segment Test (FAST) method. Although their method was faster than any detection algorithm but it has precision problems. Also, since FAST method is used only for detection, it lacks the ability to deal with image feature points that represent major issue for obtaining other main level descriptors like objects and surfaces [11].

Despite these developments, CBIR is still not effective enough especially in applications that maintain large databases of images [19]. In order to address this setback, the clustering technique is mostly used to reduce the time of search space and provide accurate matching in large databases, which means improving the indexing scheme (efficient indexing and fast searching) [24]. A new CBIR system based on color and shape features combining with k-mean clustering algorithm was proposed by Shefalli and Jindal in [17]. The results of Jindal's system proved that the method is efficient in terms the accuracy and it reduced the time of retrieval.

3. The proposed method

This work proposes a new CBIR approach that relies on a hybrid clustering method resulting from combine Artificial Bee Colony (ABC) and k-means clustering algorithms. The proposed CBIR approach supports color and texture features to describe the visual contents of images. The work employs three descriptor methods to extract the color features. The first is color histogram for HSV color space when the levels of H, S, and V are 16, 4, and 4 respectively. The second is color histogram for opponent color space while the third is the color moment. For the texture extraction methods, they are Gabor filters and ranklet transform method for RGB color space. The color moments method is only used to calculate the mean, standard deviation and skewness moments for the coefficients of the ranklet transform method. The aims of applying the hybrid clustering method are: i) to narrow the search space thereby reduce the computation time of the comparison between the feature of image query and features of all images in database, where after clustering no need to compare the image query with all images in database. ii) Enabling a more efficient clustering of image dataset based on its features; this is help to improve the accuracy of retrieval. In the proposed hybrid algorithm, the role of k-means algorithm is to categorize the images in groups, while the ABC algorithm is utilized to enhance the clustering of K-means algorithm by supporting a global search in the whole solution space. The proposed method includes find: i) the best solution then ii) best cluster of the best solution respectively.

3.1. Color feature extraction

The color is an evident and apparent feature in the image; one of the most vastly utilized features in low level feature. Comparing with texture and shape features, color feature shows better robustness against the background complication and it is more independent to the zoom and rotation [32].

3.1.1. Color histogram

Color histogram is the most popular technique used to extract the color features. The color histogram is way to capture the colors diffusion in images where each histogram represents the number of pixels for certain color (bin) in an appropriate color space (for example RGB) [13]. Any kind of color space can be used to build color histogram.

The Equations (1) and (2) are defined to compute the color histogram for an image.

$$\boldsymbol{H(I)} = \{\boldsymbol{h[0]}, \boldsymbol{h[1]}, \boldsymbol{h[3]}, \dots\dots, \boldsymbol{h[i]} \,..\, \boldsymbol{h[n]}\} \qquad (1)$$

Where H represent the histogram for the entire image I, i is the color (bin), n total number of colors (bins), and $h[i]$ represents the number of i^{th} color in the image.

If we compare images with different sizes, it necessary to normalize the color histogram first using Eqn. H' is the histogram after normalization, and t is the total pixels in the image.

$$H'(I) = \{h'[0], h'[1], h'[3], \dots\dots, h'[i] \,..\, h'[n]\} \qquad (2)$$

$$h'[i] = \frac{h[i]}{t} \qquad (3)$$

3.1.2. Color moments

The color moment have been successfully used in content based image retrieval systems as stated in [19, 38]. The use of color moment method for color features extraction characterizes the color distribution in one dimension with three moments: Mean, variance and skewness [55].

Moment1: Mean $$\mathbf{E_i} = \sum_{j=1}^{N} \frac{1}{N} \mathbf{P_{ij}} \qquad (4)$$

Moment2: Variance $$\boldsymbol{\sigma}_\mathbf{i} = \sqrt{\left(\frac{1}{N}\sum_{j=1}^{N}(\mathbf{P_{ij}} - \mathbf{E_i})^2\right)} \qquad (5)$$

Moment3: Skewness $$\mathbf{s_i} = \sqrt[3]{\left(\frac{1}{N}\sum_{j=1}^{N}(\mathbf{P_{ij}} - \mathbf{E_i})^3\right)} \qquad (6)$$

Where $\boldsymbol{E_i}, \boldsymbol{\sigma_i}$ $\boldsymbol{and}$ $\boldsymbol{s_i}$ are the mean, variance and skewness respectively. $\boldsymbol{P_{ij}}$ is the image pixel, $\boldsymbol{i}$ is the channel of image ($\mathbf{1} \le \boldsymbol{i} \le \mathbf{3}$), $\boldsymbol{j}$ is the pixel index ($\mathbf{1} \le \boldsymbol{j} \le \boldsymbol{N}$), and $\boldsymbol{N}$ is the number of pixels in one channel

3.2. Texture feature extraction

Texture is very significant and powerful feature to describe the image; it plays a vital role in handling the human perceptions against the surface specifications and directions [36]. Texture features are not as distinct as color features; color focuses on one pixel while texture is a group of neighboring pixels with frequencies in their intensity. In other words, texture is the region or spatial domain of the image which has many regular or random differences in the color value, such that it generates various 'rough' and 'smooth' patterns [39].

3.2.1. Gabor filters

Gabor filter (GF) is extensively used for extracting image texture features [15]. GF can be defined as a combination of wavelets; each wavelet captures the energy at a specific frequency and orientation. Moreover, the GF are capable capturing the whole energy of an image or a signal. Typically, I(x,y), an input image with size P × Q, is convolved with a 2D Gabor function $g_{mn}(x,y)$, to obtain a Gabor feature $G_{mn}(x,y)$using the following equation:

$$G_{mn}(x,y) = \sum_{x_1}\sum_{y_1} I(x_1,y_1)\, g_{mn}{}^{*}(x-x_1, y-y_1) \qquad (7)$$

Where * indicates the complex conjugate.

A 2D Gabor function $g(x,y)$ has its form as:

$$g(x,y) = \frac{1}{2\pi\sigma_x\sigma_y} exp[-\frac{1}{2}\left(\frac{x^2}{\sigma_x}+\frac{y^2}{\sigma_y}\right) + 2\pi jWx] \qquad (8)$$

Where $g_{mn}(x,y)$ is a set of self-similar functions generated from dilation and rotation of the Gabor function $g(x,y)$ [27]. σ_x and σ_y are the standard deviations of the Guassian envelopes along the x and y direction.

$$g_{mn}(x,y) = a^{-m} g(x',y') \qquad (9)$$

$$x' = a^{-m}(xcos\theta + ysin\theta), \;\; y' = a^{-m}(-xsin\theta + ycos\theta) \qquad (10)$$

Where m, n represent the scale and orientation respectively (m = 1,2,…,M; n = 1,2…,N), $\theta = n\pi/N$, M, N are the number of scales and orientations respectively, a>1, a^{-m} is scale factor to ensure that energy is independent of the frequency m.

We can obtain a set of magnitudes by applying Gabor filters on the image I(x, y) with different orientation at different scale as shown in Eqn. (11):

$$E(m,n) = \sum_x\sum_y |G_{mn}(x,y)| \qquad (11)$$

The mean μ_{mn} and standard deviation σ_{mn} of the magnitude of the transformed coefficients will calculated by the Eqn. (12):

$$\mu_{mn} = \frac{E(m,n)}{P\times Q}, \quad \sigma_{mn} = \frac{\sqrt{\sum_x\sum_y(|G_{mn}(x,y)| - \mu_{mn})^2}}{P\times Q} \qquad (12)$$

The Gabor feature vector is given as:

$$f = [\sigma_{11}, \sigma_{12}, \ldots, \sigma_{MN}] \qquad (13)$$

3.2.2. Ranklet transform

The Ranklet transform texture method is one of the methods used for pattern recognition especially in face detection [53]. This method has been used also in 3D structures and motion objects [54], the mammograms device to detect tumours [29], texture classification [49] and point tracking. The ranklet transform depends upon three major specifications which are nonparametric, orientation-selective, and multi-resolution.

The nonparametric property bases on measuring the local intensity of image using the order of intensity instead of the intensity itself [47]. Let I be an image, $I = [18\ 5\ 22\ 13]$, then $\pi(I) = [3\ 1\ 4\ 2]$, where $\pi(I)$ is the rank transform of image I, the range of $\pi(I)$ is [1 to m], where m is the dimension of I, [1 to m*n] for two dimensional image. The orientation-selective property means that the ranklet transform provides coefficients for different orientations (vertical, horizontal and diagonal), along the lines of Haar wavelets [8]. Two statistics that can be used to obtain the ranklet coefficients namely Wilcoxon test [25] and MannWhitney test [28].

To illustrate ranklet transform feature extraction, let P is a 2D image (m*n), N = m*n, where N is the number of pixels in P. The N pixels are then divided into two subsets: T(treatment) and C(control) for each orientation as denoted in Figure 2.11. Thus r pixels for T and k pixels for C can be obtained, where r = k = N/2. To calculate MannWhitney (W_{XY}) test by Eqn. (16), first we compute the rank transform ($\pi(P)$) and then compute the Wilcoxon (W_P) test by Eqn. (14):

$$W_p = \sum_{i=0}^{N} \pi_i V_i \qquad (14)$$

W_P is the Wilcoxon test for image P, π_i is the rank of element i,

$$V_i = \begin{cases} 0, & \pi_i \in C \\ 1, & \pi_i \in T \end{cases} \qquad (15)$$

$$W_{XY} = W_P - \frac{r(r+1)}{2} \qquad (16)$$

After that, the ranklet coefficients R_j can be calculated by the following equation:

$$R_j = \frac{W_{XY}^{j}}{rk/2} \qquad (17)$$

Where j represents the orientations (vertical, horizontal and diagonal)

3.3. Color spaces

The color space is a mathematical representation of colors in image. In this work, we will use three color spaces namely RGB, HSV and opponent. RGB color space is a three dimensional representation that consists of three main colors (Red, Green, Blue), each color is considered as a dimension for the image. The HSV color space is widely utilized in computer graphic, where it supports the Hue, Saturation and Value colorimetric characteristics. To convert the color space from RGB to HSV, the following is formula used and is defined as in Eqns. 18-20:

$$H = \cos^{-1}\left(\frac{\frac{1}{2}(2R - G - B)}{\sqrt{(R-G)^2 - (R-B)(G-B)}}\right) \quad (18)$$

$$S = 1 - \frac{3 * Min(R, G, B)}{R + G + B} \quad (19)$$

$$V = \frac{R + G + B}{3} \quad (20)$$

Where (H, S, V, R, G and B) are hue, saturation, value, red, green and blue, respectively. The opponent color space uses opponent color axes (R-G, 2B-R-G, R+G+B). This representation has the advantage of isolating the brightness information on the third axis. The following equation is used to convert RGB image to opponent (RG-BY-WB) image.

$$\begin{bmatrix} RG \\ BY \\ WB \end{bmatrix} = \begin{bmatrix} 1 & -1 & 0 \\ -1 & -1 & 2 \\ 1 & 1 & 1 \end{bmatrix} \times \begin{bmatrix} R \\ G \\ B \end{bmatrix} \quad (21)$$

Both HSV and RG-BY-WB color spaces are perceptual because they reflect how the human eyes perceive colors [51, 52].

3.4. k-means clustering algorithm

K-means clustering is one of the popular clustering methods; it is based on the number and centers of clusters [22]. This algorithm is widely used because its simplicity and efficiency [37]. From the name, k-means clusters the data object into a predetermined number of clusters (k). Each object belongs to particular cluster on the basis of calculating the sum of the square distance between each point and the centroid of that cluster. In our proposed CBIR, k-means algorithm attempts to minimize the Euclidean distance between the feature vectors of images and their centroids fast and simply. The k-means algorithm steps are illustrated as listed below. Figure 1 clarifies the steps of the algorithm by flowchart.

Input: k (number of clusters), set of patterns.

Output: the clustered patterns

Step1: Determining the number of clusters (K).

Step2: From patterns, choosing the position of clusters randomly.

Step3: Calculate the centroids of clusters using the Eqn.22.

$$m_k = \frac{1}{n_k} \sum_{\forall z_p \in C_k} z_p \qquad (22)$$

Where m_k is the centroid of C_k, C_k is the k^{th} cluster, n_k is the number of patterns in cluster, z_p is the pattern.

Step4: Calculate the distance between the patterns and centroids using the Euclidean distance using the following equation.

$$d(z_p, m_k) = \sqrt{\sum_{d=1}^{D} (z_{pd} - m_{kd})^2} \qquad (23)$$

Where D is dimension of the vector, z_{pd} represents a feature in patterns, and m_{kd} represents the attribute of cluster k centroid.

Step5: Update the clusters information depending on the minimum distance.

Step6: Return back to implement steps 3,4,5,6 if there is no moving for patterns.

Step7: The clustered pattern as output.

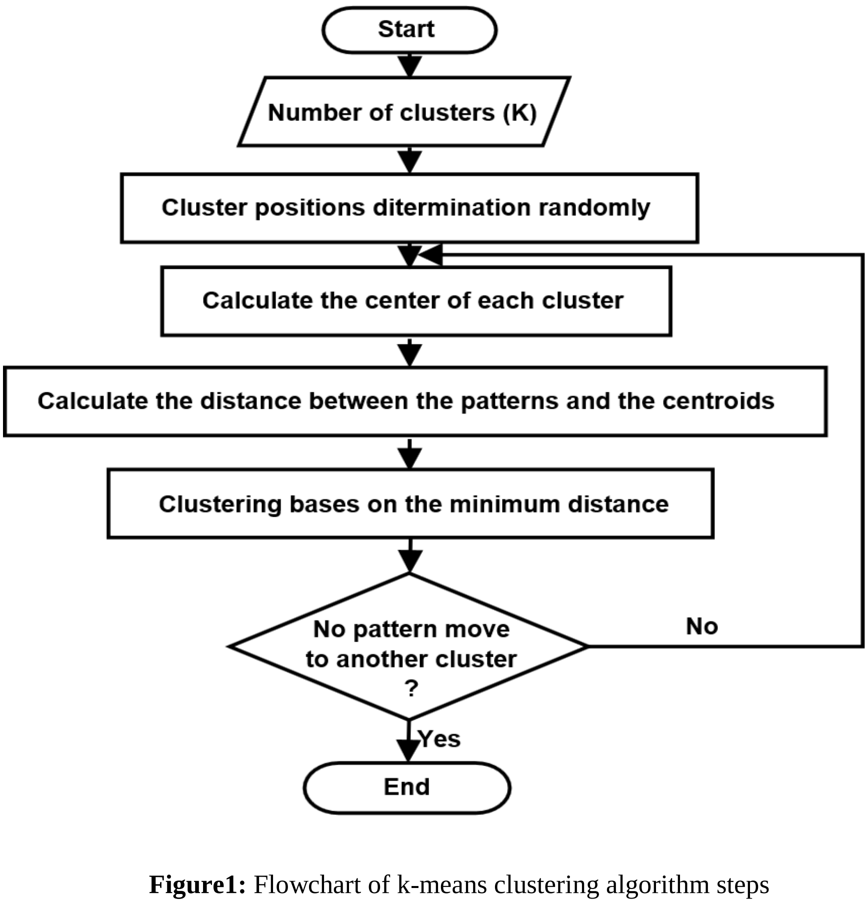

Figure1: Flowchart of k-means clustering algorithm steps

3.5. Artificial bee colony (ABC) algorithm

The ABC algorithm is a new approach and one of the swarm based algorithms that initially proposed in [20] for optimization issues. ABC simulates the intelligent behaviors that real bee colonies follow in the foraging. So far, ABC have been successfully employed in many approaches and applications such as neural networks [23], clustering [22], image processing and pattern recognition [7], and constrained optimization problems [21] etc. to solve optimization problems.

The collective intelligent search pattern for the bees includes three components: food resources, employed bees and unemployed bees (both of onlooker and scout bees) [5]. The bee colony as a whole comprises of two halves: the first represents the employed bees while the second represents the onlooker bees. There is just one employed bee for each food source. In another meaning, the number of employed bees or onlooker bees equal to the number of food sources around the hive [21]. In ABC algorithm, the food sources are considered as possible solutions for a particular problem, while the nectar amount of a food source matches up the quality (fitness) of the related solution.

At first, the ABC algorithm generates population of solutions (set of source food positions) using Eqn.24. Then, the solutions will be subjected to iterated cycles (1 to MCN) of search processes (Employed bees, onlooker bees and scout bees).

$$x_{ij} = l_i + rand(0,1) * (u_i - l_i) \qquad (24)$$

Where$i = 1,\dots,SN$; $j = 1,\dots,D$; SN represent the number of food sources and D represents the number of parameters or the dimension of the problem, u_i and l_i are respectively the upper and lower bound of the solution space of the objective function, $rand(0,1)$ is random number within the range [0, 1].

The employed bees try to find another solution (new food source) and compare it with the selected by check the nectar amount (fitness value), then keep the solution that has highest fitness and forget the other. Eqn.25 is used to generate the new solution from the old one. After complete, the employed bees share their current information about the quality and positions of the food sources with their hive mate [20]. The onlooker bees receive the food source information from the employed bees and produce new solution from the current depending on the fitness probability of the local food source. Then like the employed bee, they keep the one which has the highest fitness and forget the other. The probability (P_i) of the source foods can be calculated by the Eqn.26.

$$n_{ij} = x_{ij} + \emptyset_{ij}\,(x_{ij} - x_{kj}) \qquad (25)$$

Where n_{ij} is the new food source, j and k are the parameter and the neighbor respectively (chosen randomly), i represents the current food source, where $i \neq k$, $\emptyset_{ij}$ is random value between -1 and 1.

$$P_i = \frac{fitness_i}{\sum_{j=1}^{SN} fitness_j} \qquad (26)$$

Where

$$fitness_i = \begin{cases} \dfrac{1}{1+\ fit_i}\ , & fit_i \geq 0 \\ 1 + abs(fit_i)\ , & fit_i < 0 \end{cases} \qquad (27)$$

The scout bees change the current food source to a new one if it is abandoned for many times (exceeds limit parameters). Figure 2 shows the pseudo code of ABC algorithm in detail [21].

```
1: Initialize the population of solutions x_{i,j} , i = 1 ... SN,   j = 1… D
2: Evaluate the population
3: cycle=1
4: repeat
5:     Produce new solutions υi,j for the employed bees by using (19) and evaluate them
6:     Apply the greedy selection process
7:     Calculate the probability values P_{i,j}  for the solutions x_{i,j} by (20)
8:     Produce the new solutions v_{i,j} for the onlookers from the solutions x_{i,j} selected
       depending on P_{i,j}  and evaluate them
9:     Apply the greedy selection process
10:    Determine the abandoned solution for the scout, if exists, and replace it with a
        new randomly produced solution x_{i,j} by (18)
11:    Memorize the best solution achieved so far
12:    cycle=cycle+1
13: until cycle=MCN
```

Figure 2: Pseudo code of the ABC algorithm

3.6. Hybrid clustering (ABC – K-means) algorithm

The hybrid clustering algorithm is basically an integration of the Artificial Bee Colony algorithm and the k-means clustering algorithm; it combines the benefit of both algorithms. ABC algorithm applies a global search in the solution space while the k-means adopts the local search.

The proposed hybrid clustering uses the ABC algorithm to improve the ability of k-means algorithm to get the optimum clustering.

Step1 (Initialization): this step involves the following sub steps:

a) Initialize the control parameters SN, MCN, K, Limit (see Table 2).
b) Initialize the source food (SN solutions) using k-means clustering algorithm to partition the images into K clusters, where the length of solution vector equal to K as in Figure 3. Then calculate the fitness for each solution using Eqn. 27.

Eqn.28 expresses the fitness function which will be used in the proposed hybrid clustering. According [56], the following function will minimize the quantization error.

$$fit(x_i, Z) = J_e * \frac{d_{max}(Z, x_i)}{d_{min}(Z, x_i)} * (d_{max}(Z, x_i) + z_{max} - d_{min}(Z, x_i) + MSE \qquad (28)$$

$d_{max}(Z, x_i)$ is to apply the intra-cluster distance criterion, And the $d_{min}(Z, x_i)$ represents the inter-cluster separation criterion as in Eqn.29 and Eqn.30 respectively. Z=$\{z_1, z_2, \dots z_p, \dots z_n\}$, where Z is set of n patterns (images) in cluster, z_p is an image as D-dimensional vector.

$$d_{max}(Z, x_i) = \max\left\{ \sum_{\forall\, z_p \in C_{i,k}} \frac{d(z_p,\ m_{i,k})}{n_{i,k}} \right\} \qquad (29)$$

$$d_{min}(Z, x_i) = \min\{d(m_{i,j}\ , m_{i,k})\}\ ,\quad j \neq k. \qquad (30)$$

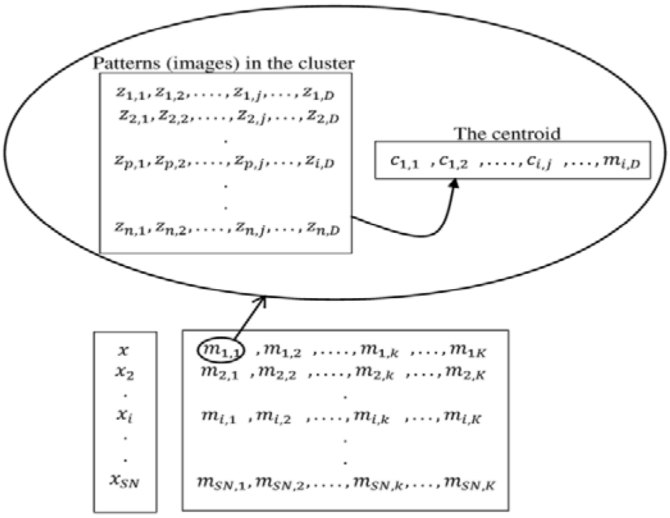

Figure 3: Population of food sources construction using the clusters

J_e is the quantization error and is expressed in the general quality of a clustering algorithm as in Eqn. 31.

$$J_e = \frac{\sum_{k=1}^{K} \sum_{\forall\, z_p \in C_k} d(z_p, m_k)/n_k}{K} \qquad (31)$$

And MSE is the mean square error and it is expressed in Eqn. 32.

$$MSE = \frac{1}{N} \sum_{k=1}^{K} \sum_{\forall\, z_p \in C_k} d(z_p, m_k)^2 \qquad (32)$$

N is the total number of patterns (images) , K is the number of clusters, m_k is centroid of k^{th} cluster, n_k number of patterns (images) in k^{th}cluster, $d(z_p, m_k)$ is the Euclidean distance between z_p and m_k.

Step2 (Employed bee stage): For each employed bee, apply k-means for the current solution to get new solution, the centroids of clusters (current solution) will updated to the new solution if its fitness value less than the fitness value of the new solution (greedy selection).

Step3 (Onlooker bee stage): For each onlooker bee, apply k-means for the current solution to get new solution. The centroids of clusters (current solution) will updated to the new solution if its probability value greater than random value (between 0 and 1), and its fitness value less than the fitness value of the new solution (greedy selection). We can calculate the probability of the solution using Eqn.26.

Step4 (Scout bee stage): For the scout bee phase, check the failures of each solution, if it exceeds the control parameter (limit), generate new solutions to replace the old one. In other word, the abandoned food source is one that cannot be improved upon after certain number of cycles, as determined by the limit parameter.

Step5: Memorize the best solution achieved so far, and repeat the steps from 2 to 5 until met the MCN.

Step6: Obtain the best solution (food source) as output.

3.7. Similarity and performance measurement

The similarity measurement computes the distance between two objects; in CBIR, it measures the distance between the query image and the images in database based on their own extracted features. If there are two similar images, that means they have few distance between them. The most commonly used similarity measures is Minkowski-form distance [16] which is defined in Eqn. (33):

$$D_p(I,J) = (\sum_{i=0}^{N-1} |f_i(I) - f_i(J)|^p)^{1/p} \qquad (33)$$

$D_p(I,J)$ represents the distance between image I and image J, N is the number of features, while i is the index of feature. When $p = 1$, it is known as city block distance or Manhattan distance. When $p = 2$, it is Euclidean distance or metric distance (most widely used in image retrieval).

To evaluate the performance of CBIR, recall and precision pair (RPP) is the most efficient method [3]. This measure has two indicators: the recall and precision. The precision evaluates the system capability in terms of retrieve only the relevant images (Eqn. 34), while recall evaluates the system capability of in terms of retrieve all the relevant images in database (Eqn. 35).

$$precision = \frac{A}{A+B} \qquad (34)$$

$$Recall = \frac{A}{A+C} \qquad (35)$$

A =number of relevant images retrieve, B =number of irrelevant images, C =number of relevant images not retrieved

3.8. Proposed CBIR scheme

The following illustrates the steps of the proposed CBIR:

The inputs: Dataset of images (search domain) and query image

The output: The most similar 10 images to the query image

Step1: Extract the color histogram for HSV image, color histogram for RG-BY-WB image, Gabor and ranklet transform features of all images in database, thus, a database of feature vectors for all images will be obtained.

Step2: Choose one image as query image from the dataset of images (already its four features are extracted).

Step3: cluster the features of images using the proposed hybrid algorithm (ABC-k-means). The output of this step is the best solution which contains 10 clusters of images.

Step4: Calculate the distance between the query image and the centroids of each cluster in the best solution using Eqn. (233) to find the best cluster, where the best cluster has the least distance.

Step5: Apply the Step3 and Step4 on each of the features that mentioned in step1, and then integrate the best clusters in one cluster.

Step6: Calculate the similarity between the query image and each image that follow to the cluster that obtained from Step6 using Eqn. (36).

$$D_{final} = w_1 \times D_1(I,J) + w_1 \times D_2(I,J) + w_1 \times D_3(I,J) + w_1 \times D_4(I,J) \qquad (36)$$

Where I is the query image, J is the image in cluster, D_{final} is the final distance between I and J. D_1, D_2, D_3 and D_4 are the distance between I and J depending on color histogram (HSV), color histogram (RG-BY-WB), Gabor filters and ranklet transform features respectively.

Step7: retrieve the 10 images that are most similar to the query image. The proposed CBIR is as shown in Figure 4.

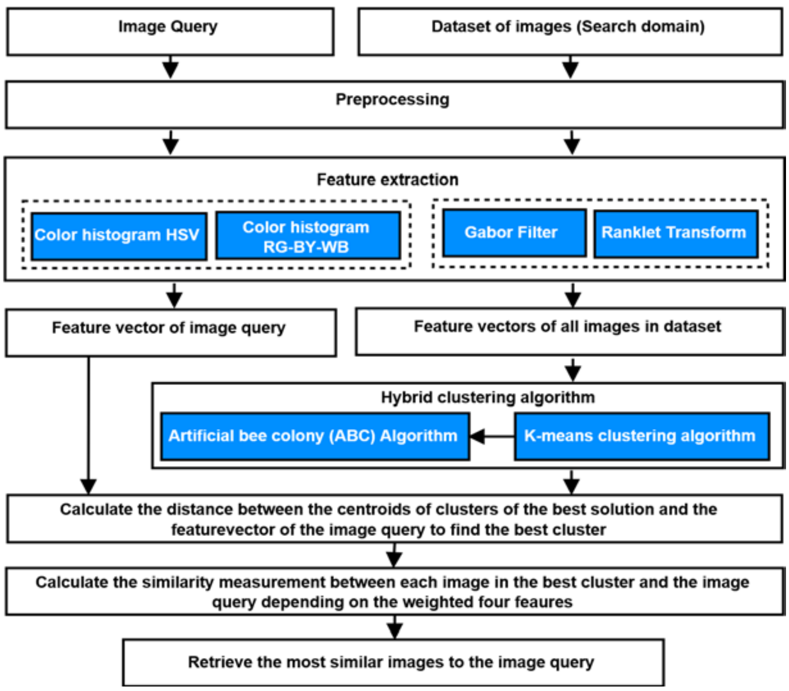

Figure 4: The Proposed CBIR Scheme

4. Results and Discussions

The experimental results of the proposed method is presented and discussed in this section. The discussion of results shall follow the steps outlined in section 3 based on the methodology presented in Figure 1 of the previous section; data preparation, feature extraction, apply the hybrid clustering algorithm (feature indexing), similarity measurement and retrieval of the results. The proposed method's performance is evaluated by comparing the retrieved results with the results of a prior work in the same field; it is [46].

4.1 Data preparation and parameter settings

WANG dataset was used in conducting this experiment; this dataset is a subset of 1000 images of the Corel database which is manually selected and comprises of 10 categories, each category has 100 images. Table 1 shows the categories of image dataset used for this study.

Table 1: Categories of image dataset

Category No.	Category name	Number of images	Range of images
1	Africa people and villages	100	0-99
2	Beaches	100	100-199
3	Buildings	100	200-299
4	Buses	100	300-399
5	Dinosaurs	100	400-499
6	Elephants	100	500-599
7	Flowers	100	600-699
8	Horses	100	700-799
9	Mountains and glaciers	100	800-899
10	Food	100	900-999

Before apply the proposed method, several parameters was used. The parameters are shown in table 2.

Table 1: The parameters and values used in the proposed system

Parameter		Value
K-means	Number of clusters (K)	10
ABC	Maximum cycle number(MCN)	10
	Number of solutions (SN)	25
	Triggering threshold (limit)	3
Similarity measurement	The weight used in color histogram (HSV) features (w1)	0.41
	The weight used in color histogram (RG-BY-WB) features (w2)	0.28
	The weight used in Gabor filter (RGB) features (w3)	0.07
	The weight used in Ranklet transform (RGB) features (w4)	0.24

4.2 Evaluation of the Proposed Method

To test the retrieval effectiveness, we choose 4 images from various classes arbitrarily (each one is as an image query). Then retrieve the 10 most similar images to the query image. The first test case used is the African people and villages category using image 40.jpg. The system retrieved 10 images that were all relevant to the query image as shown in the Figure 5.

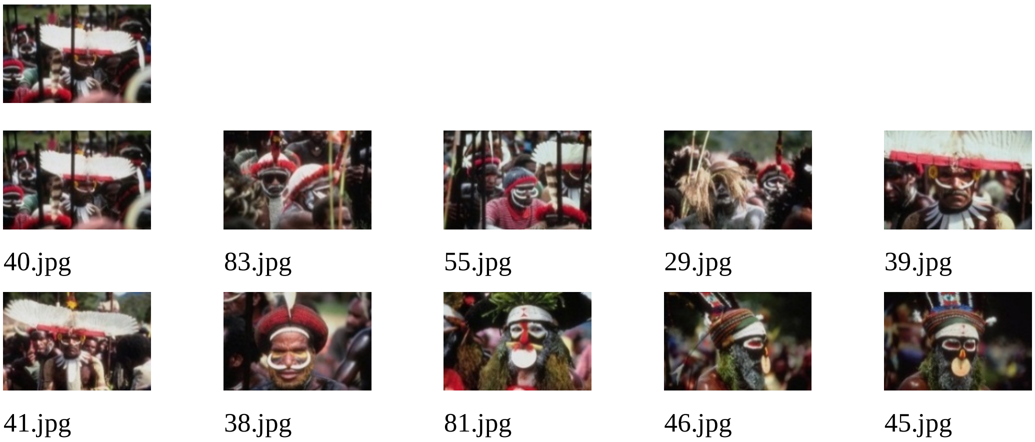

Figure5: Top 10 retrieved images of African people and villages

The second test case used is the Dinosaur category (image 484.jpg) as illustrated in Figure 6. The number of relevant images retrieved is 10.

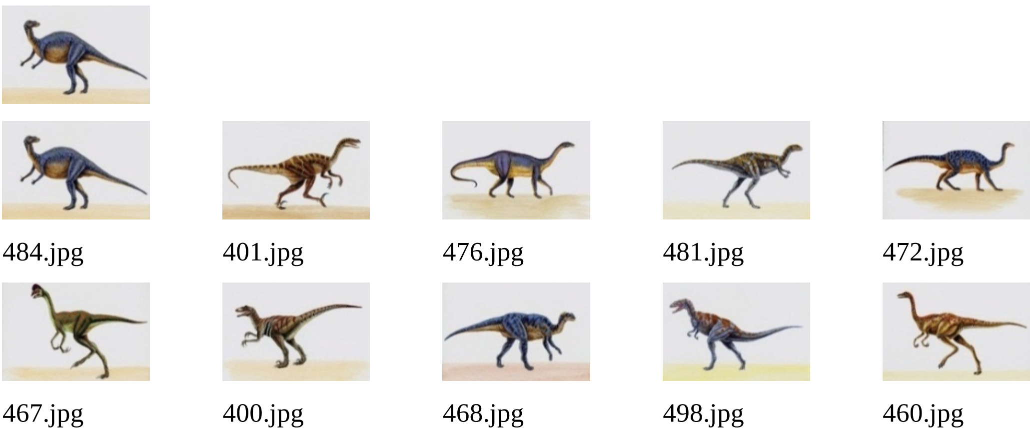

Figure 6: Top 10 retrieved images of Dinosaurs

The third test case is the Flowers category. Figure 7 shows that the system retrieved 10 relevant images similar to the query image.

Figure 8 shows the fourth test result of the proposed method for images of the Mountains category, which image query is 881.jpg. Two images (150.jpg and 166.jpg) are irrelevant but similar to the query image.

Also, the precision and recall measurement is used to evaluate the proposed CBIR system. To calculate the precision and recall, we used all the images in each category as queries. For example, we used all the 100 images in each class; that means we got 100 precision for each category. Furthermore, the number of images retrieved from each on search (by one image query) is 10 images. And thus, the total precision for each category (calculated by Eqn.37) correspond the average of all precisions; same case for recall (calculated by Eqn.38).

Figure7: Top 10 retrieved images of Flowers

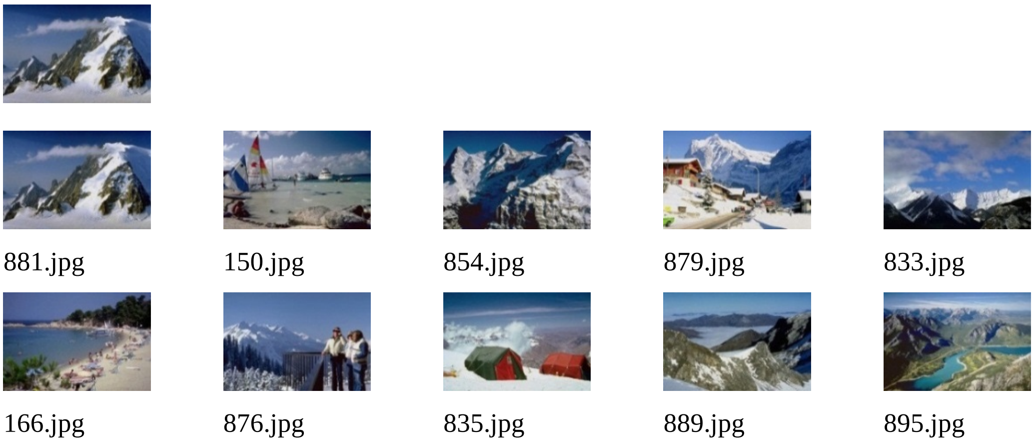

Figure 8: Top 10 retrieved images of Mountains

$$p'_c = \sum_{i=1}^{100} p(I_i) / 100 \qquad (37)$$

$$r'_c = \sum_{i=1}^{100} r(I_i) / 100 \qquad (38)$$

Where p' and r' are the total precision and total recall respectively, c is the category (1-10), i is the index of image in certain category, $p(I_i)$ and $r(I_i)$ are the precision and recall respectively when the image query is I. Figure 9 shows the total precision and recall of the proposed method. The maximum precision average for Dinosaurs is 0.999; its recall is 0.968. While the minimum precision for Mountains is 0.52; its recall is 0.289.

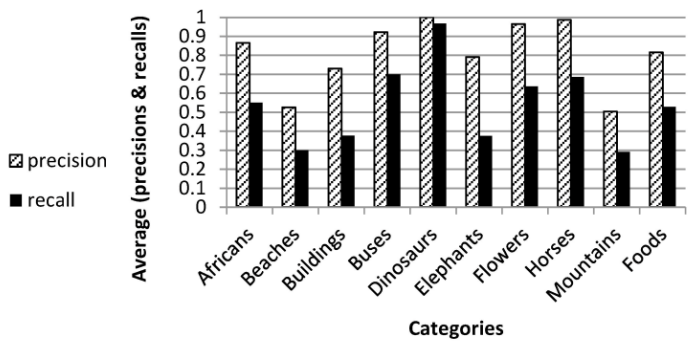

Figure 9: Precision and recall of the proposed method

Figure 10 shows the averages of the total precisions and recalls for all classes when the total numbers of images retrieved are 20,40,60,80 and 100.

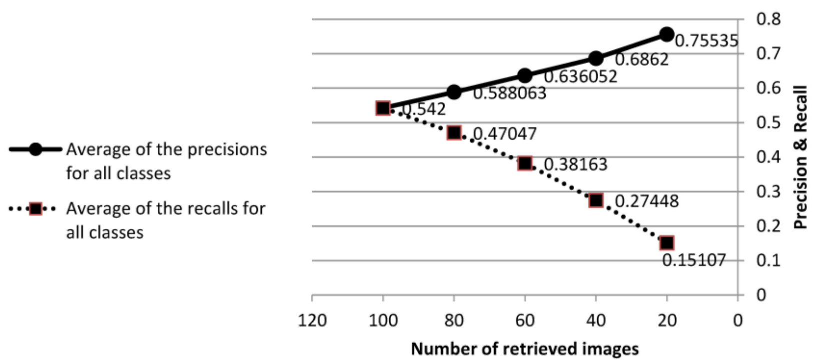

Figure 10: The average of precisions and recalls of all classes for different numbers of retrieved images

4.3 Validation of the Proposed Method

The proposed method was compared with the existing method [46] in terms of the precision. The choice of this particular method as a benchmark for this study was based on the fact that the study results of Younus *and his colleagues* have been shown to be more superior to other previous methods based on the findings of their study. Thus, since it is a superior method in terms of precision when compared to previous works, it will be an appropriate benchmark for this study. Also, their study employed the precision-recall measure, which besides being a good performance evaluator, is also the same evaluation measurement used for this study. In [45], the authors pointed out that comparing the performance of two CBIR methods is an improper unless those methods use same the evaluation measurement. In order to properly validate the proposed method, several criteria are compared with the existing method and selected as a benchmark for this study. These criteria include: 1) the clustering), 2) Wang dataset, 3) total number of image retrieved (10), 4) performance measure (precision-recall). Table 9 presents the precision values of each images subset for both the proposed and existing methods and also the difference between them; where A is the existing method, B is the proposed method and |A-B| is the difference between the two methods. Figure 11 illustrates the result of comparison between the proposed and existed method.

Table 3: The proposed and existing methods precision comparison

The Category	[58] PSO + k-means (A)	The proposed method ABC + k-means (B)	|A-B|
Africa people and villages	0.890	0.864	0.026
Beaches	0.730	0.525	0.205
Buildings	0.701	0.729	0.028
Buses	0.838	0.921	0.083
Dinosaurs	0.998	0.999	0.001
Elephants	0.795	0.790	0.005
Flowers	0.925	0.963	0.038
Horses	0.871	0.985	0.114
Mountains and glaciers	0.550	0.502	0.048
Food	0.755	0.815	0.060
Average	0.8053	0.8093	0.04

Table 3 demonstrates that the performance of the proposed method outperforms the existing method in six categories: Buildings, Buses, Dinosaurs, Flowers, Horses and Foods. For the Africans and Elephant categories, there is an approximation between the two methods while there is more difference in the beaches and the mountains categories. This high difference can be attributed to two reasons; firstly, the similarity between these two categories is because their features are similar, therefore, it is very important to look for another feature like the shape feature to ensure proper categorization. Secondly, the extraction process of more than one feature by itself is difficult because each category of images contain features that disparately differ from the other categories. Therefore, the amount of adjustment on each feature negatively or positively affects some categories. In general, based on the validation results, the proposed method showed better result in terms of the precision for six categories at the expense of less precision for four categories. Also from the results presented in Table 9, it can be seen that the sum average for all categories between the two methods is 0.8093 for the proposed methods while that of the existing method is 0.8053, with a sum difference of 0.04 in favor of the proposed method. Thus, the result is showing that the proposed method yields a higher precision result in CBIR and it is superior to the existed CBIR method in terms of accuracy.

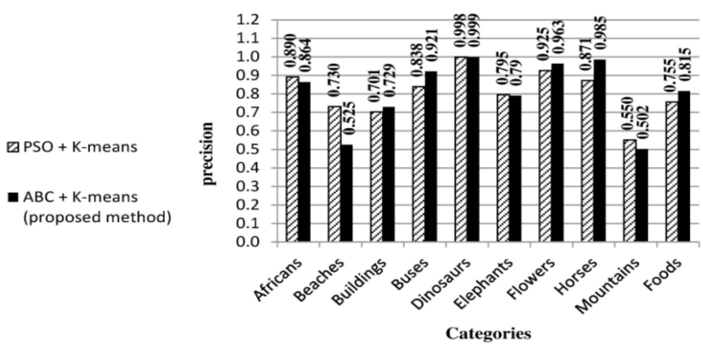

Figure 11: The Graph of precision and recall of the proposed CBIR

5. Conclusion

This study proposed a new hybrid method for content-based image retrieval using a combination of (ABC + k-means) algorithms. The k-means clustering algorithm has some setbacks, one of which is that it does not generate optimal clustering because it bases on an initial cluster centroids [35]. The proposed hybrid method addressed this setback by integrate the ABC technique with the k-means algorithm. In the proposed hybrid algorithm, the role of k-means algorithm is to categorize the images to groups, while the ABC algorithm is utilized to enhance the clustering of K-means algorithm by supporting a global search in the whole solution space. As a consequence, the proposed hybrid technique (ABC + k-means) helped to narrow the search space thereby reducing the computation time consumed to compare all images in database with the image query. Also, it produced a more efficient clustering for the color and texture features of the images, while at the same time supporting a global search in the whole solution space; this also helped improve the accuracy of retrieval.

After evaluation, the proposed method proved to be more superior to the existing method in terms of the precision. The major limitation of this study is that the features of image used in the work are limited to only the color and texture description.to tackling this limitation, we can update the proposed system to support shape feature in addition to the color and texture features. Also, the use of tools like segmentation, to extract the meaningful and desired features should be investigated. Furthermore, we can take in account the human interaction availability (relevant feedback) to develop robust CBIR system.

References

[1] A. Ahmadyfard and H. Modares, "Combining PSO and k-means to Enhance Data Clustering," in Telecommunications, 2008. IST 2008. International Symposium on, 2008, pp. 688-691.

[2] P. Alshuth, et al. , "Iris-image retrieval for images and videos," 1996.

[3] G. P. Babu, et al., "Color indexing for efficient image retrieval," Multimedia Tools and Applications, vol. 1, pp. 327-348, 1995.

[4] J. R. Bach, et al., "Virage image search engine: an open framework for image management," in Electronic Imaging: Science & Technology, 1996, pp. 76-87.

[5] L. Bao and J.-c. Zeng, "Comparison and analysis of the selection mechanism in the artificial bee colony algorithm," in Hybrid Intelligent Systems, 2009. HIS'09. Ninth International Conference on, 2009, pp. 411-416.

[6] M. BENČO and R. Hudec, "Novel method for color textures features extraction based on GLCM," Radioengineering, vol. 4, pp. 64-67, 2007.

[7] C. Chidambaram and H. S. Lopes, "A new approach for template matching in digital images using an artificial bee colony algorithm," in Nature & Biologically Inspired Computing, 2009. NaBIC 2009.

World Congress on, 2009, pp. 146-151.

[8] I. Daubechies, Ten lectures on wavelets vol. 61: SIAM, 1992.

[9] B. Dinakaran, et al., "Interactive image retrieval using text and image content," Cybern Inf Tech, vol. 10, pp. 20-30, 2010.

[10] G. Duan, et al., "Content-Based Image Retrieval Research," Physics Procedia, vol. 22, pp. 471-477, 2011.

[11] M. El-gayar and H. Soliman, "A comparative study of image low level feature extraction algorithms," Egyptian Informatics Journal, vol. 14, pp. 175-181, 2013.

[12] M. Flickner, et al., "Query by image and video content: The QBIC system," Computer, vol. 28, pp. 23-32, 1995.

[13] R. Gonzalez and R. Woods, "Digital Image Processing," Addision-Wesley,Reading MA, 1992.

[14] E. Hancer, et al., "Artificial Bee Colony based image clustering method," in Evolutionary Computation (CEC), 2012 IEEE Congress on, 2012, pp. 1-5.

[15] Z.-C. Huang, et al., "Content-based image retrieval using color moment and Gabor texture feature," in Machine Learning and Cybernetics (ICMLC), 2010 International Conference on, 2010, pp. 719-724.

[16] H. Jiawei and M. Kamber, "Data mining: concepts and techniques," San Francisco, CA, itd: Morgan Kaufmann, vol. 5, 2001.

[17] S. Shefalli and B. Jindal, "Enhancing Content-based Image Retrieval using Moving K-Means Clustering Algorithm", International Journal of Computer Applications, vol. 102, no. 9, pp. 31-37, 2014.

[18] L. Jinxia and Q. Yuehong, "Application of SIFT feature extraction algorithm on the image registration," in Electronic Measurement & Instruments (ICEMI), 2011 10th International Conference on, 2011, pp. 177-180.

[19] A. Kannan, et al., "Image clustering and retrieval using image mining techniques," IEEE International Conference on Computational Intelligence and Computing Research, vol. 2, 2010.

[20] D. Karaboga, "An idea based on honey bee swarm for numerical optimization," Technical report-tr06, Erciyes university, engineering faculty, computer engineering department2005.

[21] D. Karaboga and B. Basturk, "Artificial bee colony (ABC) optimization algorithm for solving constrained optimization problems," in Foundations of Fuzzy Logic and Soft Computing, ed: Springer,

2007, pp. 789-798.

[22] D. Karaboga and C. Ozturk, "A novel clustering approach: Artificial Bee Colony (ABC) algorithm," Applied soft computing, vol. 11, pp. 652-657, 2011.

[23] D. A. Karaboga, "Artificial bee colony (ABC) algorithm on training artificial neural networks," Signal Processing, 2007.

[24] S. Krishnamachari and M. Abdel-Mottaleb, "Hierarchical clustering algorithm for fast image retrieval," in Electronic Imaging'99, 1998, pp. 427-435.

[25] E. Lehmann, "Nonparametric Statistical Methods Based on Ranks," ed: San Francisco, CA: Holden-Day, 1975.

[26] W.-Y. Ma and B. S. Manjunath, "Netra: A toolbox for navigating large image databases," Multimedia systems, vol. 7, pp. 184-198, 1999.

[27] B. S. Manjunath and W.-Y. Ma, "Texture features for browsing and retrieval of image data," Pattern Analysis and Machine Intelligence, IEEE Transactions on, vol. 18, pp. 837-842, 1996.

[28] H. B. Mann and D. R. Whitney, "On a test of whether one of two random variables is stochastically larger than the other," The annals of mathematical statistics, pp. 50-60, 1947.

[29] M. Masotti, "A ranklet-based image representation for mass classification in digital mammograms," Medical physics, vol. 33, pp. 3951-3961, 2006.

[30] A. Pentland, et al., "Photobook: Content-based manipulation of image databases," International journal of computer vision, vol. 18, pp. 233-254, 1996.

[31] B. E. Prasad, et al., "A microcomputer-based image database management system," Industrial Electronics, IEEE Transactions on, pp. 83-88, 1987.

[32] P. Reddy and K. S. Prasad, "Color and texture features for content based image retrieval," International Journal of Computer Technology Application, vol. 2, pp. 1016-1020, 2011.

[33] E. Rosten and T. Drummond, "Fusing points and lines for high performance tracking," in Computer Vision, 2005. ICCV 2005. Tenth IEEE International Conference on, 2005, pp. 1508-1515.

[34] Y. Rui, et al, "Image Retrieval: Current Techniques, Promising Directions, and Open Issues", Journal of Visual Communication and Image Representation, vol. 10, no. 1, pp. 39-62, 1999.

[35] G. Serban and G. S. Moldovan, "A comparison of clustering techniques in aspect mining," Informatica, vol. 51, 2006.

[36] S. A. Shafer, "Texture Representations for Image Retrieval," The George Washington University, 2012.

[37] P. Vora and B. Oza, "A survey on k-mean clustering and particle swarm optimization," Int. J. Sci. Modern Eng, vol. 1, pp. 24-26, 2013.

[38] 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, 1997, pp. 87-98.

[39] C. Solomon and T. Breckon, Fundamentals of Digital Image Processing: A practical approach with examples in Matlab: John Wiley & Sons, 2011.

[40] M. J. Swain and D. H. Ballard, "Color indexing," International journal of computer vision, vol. 7, pp. 11-32, 1991.

[41] B. Thomee and M. S. Lew, "Interactive search in image retrieval: a survey," International Journal of Multimedia Information Retrieval, vol. 1, pp. 71-86, 2012.

[42] B. K. Verma and D. Kumar, "A review on Artificial Bee Colony algorithm," International Journal of Engineering & Technology, vol. 2, pp. 175-186, 2013.

[43] X.-Y. Wang, et al., "Content-based image retrieval by integrating color and texture features," Multimedia Tools and Applications, vol. 68, pp. 545-569, 2014.

[44] J.-K. Wu, et al., "CORE: a content-based retrieval engine for multimedia information systems," Multimedia systems, vol. 3, pp. 25-41, 1995.

[45] B. Xue and L. Wanjun, "Research of image retrieval based on color," in Computer Science-Technology and Applications, 2009. IFCSTA'09. International Forum on, 2009, pp. 283-286.

[46] Z. S. Younus, et al., "Content-based image retrieval using PSO and k-means clustering algorithm", Arabian Journal of Geosciences, vol. 8, no. 8, pp. 6211-6224, 2014.

[47] R. Zabih and J. Woodfill, "Non-parametric local transforms for computing visual correspondence," in Computer Vision—ECCV'94, ed: Springer, 1994, pp. 151-158.

[48] D. Zhang, et al., "Content-based image retrieval using Gabor texture features," in IEEE Pacific-Rim Conference on Multimedia, University of Sydney, Australia, 2000.

[49] M. Masotti and R. Campanini, "Texture classification using invariant ranklet features," Pattern Recognition Letters, vol. 29, pp. 1980-1986, 2008.

[50] Y.-H. Lee, et al., "Efficient Image Retrieval Using Advanced Clustering SURF," in Network-Based

Information Systems (NBiS), 2012 15th International Conference on, 2012, pp. 749-753

[51] J. Zhang, et al., "A color indexing scheme using two-Level clustering processing for effective and efficient image retrieval," in Proceedings of the 2005 International Conference on Data Mining (DMIN'05), 2005, pp. 73-78.

[52] X. Li, et al., "An effective content-based visual image retrieval system," in Computer Software and Applications Conference, 2002. COMPSAC 2002. Proceedings. 26th Annual International, 2002, pp. 914-919.

[53] F. Smeraldi, "Ranklets: orientation selective non-parametric features applied to face detection," in Pattern Recognition, 2002. Proceedings. 16th International Conference on, 2002, pp. 379-382.

[54] A. Del Bue, et al., "Non-rigid structure from motion using ranklet-based tracking and non-linear optimization," Image and Vision Computing, vol. 25, pp. 297-310, 2007.

[55] M. A. Stricker and M. Orengo, "Similarity of color images," in IS&T/SPIE's Symposium on Electronic Imaging: Science & Technology, 1995, pp. 381-392.

[56] C. Ozturk, et al., "Improved clustering criterion for image clustering with artificial bee colony algorithm," Pattern Analysis and Applications, pp. 1-13, 2014.