Vol. 6(22), Oct. 2016, PP. 3110-3123

Contents list available at IJMEC

International Journal of Mechatronics, Electrical and Computer Technology (IJMEC)

Journal Homepage: www.aeuso.org

PISSN: 2411-6173 - EISSN: 2305-0543

Content Based Image Retrieval for Marine Life Images Using Ant Colony Optimization Feature Selection

Zobeir Raisi* and Javad Azarakhsh

Chabahar, Maritime University, Chabahar, IRAN

Phone Number: *+98-915-3461040*

****Corresponding Author's E-mail:*** *zobeir.raisi@cmu.ac.ir*

Abstract

The main aim of this paper is to apply the content based image retrieval techniques to provide new services for marine life images. For this purpose, a marine life images database is created. Then three particular content-based image retrieval techniques are selected and applied to this database. The first image feature is based on color and is called color moment and HSV color histogram, the second and third image features, called gray low level co-occurrence matrix (GLCM) and Zernike moments (ZM), are based on texture and shape features, respectively. The experimental results showed that the image retrieval method based on multi-feature fusion has better retrieval performance than using only single feature. Then To achieve higher retrieval performance The Ant Colony Optimization Feature selection (ACOFS) is proposed. The simulation results showed that by applying ACOFS image retrieval system, not only could the number of features be effectively reduced, but higher image retrieval accuracy is achieved.

Keywords: *Image Retrieval, Marine life, feature extraction, Ant Colony Optimization, Feature Selection*

1. Introduction

Different forms of image resources are rapidly growing with a huge development of rapid development and popularization of digital technology, computer and network technology ,visual contents of image and technologies, e.g. image data in smart phones, world wide web , communication, etc. [1]–[5]. Therefore efficient indexing and searching becomes an important problem from growing image databases. Traditional text-based image retrieval technology is rarely used because it requires artificial annotation by the line and the image database is huge; so, content-based image retrieval (CBIR) system is getting more and more attention of people, it has become a hot research topic [3], [6]–[10]. CBIR is a technique for retrieving similar images for a particular query image from a large image dataset. Many schemes have been developed to solve and improve the retrieval accuracy of the content-based image retrieval [11]. Three low level visual features of images, such as color, shape and texture feature have been used to explore the features in CBIR systems [12]. Color is one of the most dominant and distinguishing visual feature that is widely used visual features in CBIR and is invariant to image size and orientation [2]. The color histogram is a common technique used in image retrieval systems [9], [11].Texture is used to specify the roughness or coarseness of object surface of an image. Texture feature has been used in various applications ranging from medical imaging to industrial application [13]. Haralick et al. introduced the concept of gray level co-occurrence matrix (GLCM), and extracted statistical features for texture image classification [14].

Article History:

Received Date: Jun. 11, 2016

Accepted Date: Sep. 04, 2016

Available Online: Oct. 02, 2016

GLCM works directly with intensity of image and provides the spatial correlation of pixels in the image and hence, it is helpful in texture feature extraction. Shape is one of the basic low-level visual feature in image retrieval systems. shape features can capture the most attractive visual information, which is based on human perception [15], [16].The Zernike moments based on the theory of orthogonal polynomials is proposed by M. R. Teague [17]. Because of the Zernike moments have image rotation invariance, and it can be used for image retrieval, because it can be calculated easily.

Feature selection is one of the most fundamental problems in the field of machine learning and computer vision that has an important role in data mining. The main aim of feature selection is to reduce the dimension of original feature set by identifying the best features properly which provides the best retrieval performances. In recent years, a lot of feature selection methods have been proposed. Which are: Tabu seach[18], Simulated annealing (SA)[19], genetic algorithm (GA) [20], particle swarm optimization (PSO) [21] , Ant colony optimization (ACO) and so on [22]–[24].(ACO) is an algorithm that is inspired by social behavior of ant colonies and has already been used in many optimization problems for optimum solutions [12], [25]–[27].

For identification and classification the species group automatically without having to manually search through huge collection image database, as a new application, we propose a scenario in which CBIR system via query by example is used to categorize and differentiate the various types of marine species especially the one available in Persian Gulf. In this research, a study was carried out on three CBIR methods. The methods employed color, texture, and edge features to characterize a query image. The methods were then compared based on their accuracy, and suitability for our application. In this regard, a dataset consisting of 250 marine life images is prepared. The images are taken from 10 marine life species group in Persian Gulf and Oman Sea and obtained mainly from Google image search and contributed by Iran Fisheries organization (IFO). Figure 1 shows the studied CBIR framework in this paper.

The rest of the paper is organized as follows: in Section 2, a brief review of color shape and texture feature extraction is described. The image retrieval system is introduced in Section 3. Section 4 describes the feature selection based on ACO. Experimental results and discussions are given in Section 5. Conclusions are described in Section 6.

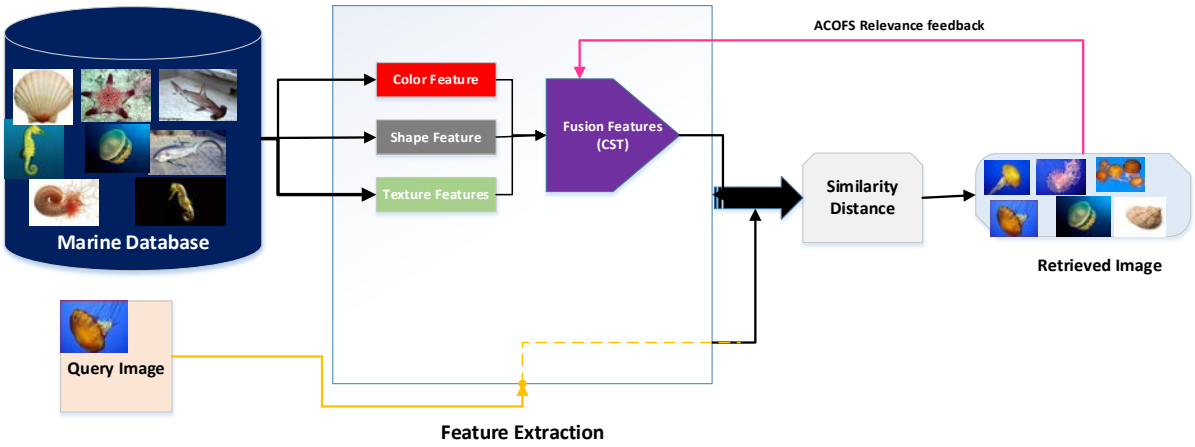


Figure 1: The proposed framework of studied CBIR

2. Feature Extraction

The features that used in this paper for image retrieval are color moments and HSV color histogram , for color feature, gray low level co-occurrence matrix (GLCM), a texture feature and Zernike Moments (ZM), a shape feature. They are summarized as follows.

2.1. Color Moments and Color Histogram

Color moment is used for representing of distribution colors in the image. Many color spaces are used for extraction the color moment, but the RGB color space has better retrieval performance in feature extraction in color moments. Three low order moments include: the first moment, second moment and third moment can express the color distribution of an image. These three low order moments are defined as follows:

$$u_i = \frac{1}{M \times N} \sum_{i=1}^{M} \sum_{j=1}^{N} p_{ij} \tag{1}$$

$$\sigma_i = \left[\frac{1}{M \times N} \sum_{i=1}^{M} \sum_{j=1}^{N} (p_{ij} - u_i) \right]^{1/2} \tag{2}$$

$$s_i = \left[\frac{1}{M \times N} \sum_{i=1}^{M} \sum_{j=1}^{N} (p_{ij} - u_i) \right]^{1/3} \tag{3}$$

The method used in this paper is color moment in RGB and Lab color spaces. Color moment features vector in both of color spaces has nine components. In our experimental result, the RGB color space has better retrieval effect than Lab color space.

The method used in this paper is color histogram in HSV color space with 72bin color histogram. the specific quantitative rules are defined as follows [28]:

$$H = \begin{cases} 0, & h \in [315,20] \\ 1, & h \in [20,40] \\ 2, & h \in [40,75] \\ 3, & h \in [75,155] \\ 4, & h \in [155,190] \\ 5, & h \in [190,271] \\ 6, & h \in [271,295] \\ 7, & h \in [295,315] \end{cases}, \quad S,V = \begin{cases} 0, & s,v \in [0,0.2] \\ 1, & s,v \in [0.2,0.7] \\ 2, & s,v \in [0.7,1] \end{cases} \tag{4}$$

The following equation is used for calculation the HSV color histogram which round is the rounding function.

$$Hsv\_Feature = round(9H + 3S + V) \tag{5}$$

2.2. Zernike Moments

In this paper, the Zernike moments are selected for shape feature extraction; they have good rotation invariance and simple calculation, at the same time they are widely used as a kind of shape

descriptor. Zernike moments are a special kind of complex moments, they are orthogonal functions based on Zernike polynomials, Zernike polynomials are orthogonal in the unit circle, and their orthogonalities make Zernike moments independent, they have large superiority in characteristic expression ability [28]. A basic function for the Zernike orthogonal polynomials are defined as follows:

$$V_{nm}(x,y) = V_{nm}(\rho,\theta) = R_{nm}(\rho)e^{jm\theta} \tag{6}$$

where n and m are the orders of the orthogonal Zernike polynomials, n is a positive integer or zero, m is a positive or negative integer, they are subject to the conditions $n - |m| = even$ and $n \geq |m|$; ρ is the vector length between circle dot and the pixel (x,y), θ is the angle between vector and the x-axis of counterclockwise direction; $R_{nm}(\rho)$ is an orthogonal radial polynomial of real value, it is defined as follows:

$$R_{nm}(\rho) = \sum_{s=0}^{(n-|m|)/2} \frac{(-1)^s [(n-s)!]\rho^{n-2s}}{s!\left(\frac{n+|m|}{2}-s\right)!\left(\frac{n-|m|}{2}-s\right)!} \tag{7}$$

Zernike moments of the image refer to the projection of image function $f(x,y)$ on the orthogonal polynomial $V_{nm}(x,y)$, n order Zernike moment with the repetition of m is defined as:

$$Z_{nm} = \frac{n+1}{\pi}\iint_{x^2+y^2\leq 1} f(x,y)V_{nm}^*(x,y)dxdy \tag{8}$$

For two dimensional images, the integrals in above equation are replaced by summations and the Zernike moments can be defined as [17]:

$$Z_{nm} = \frac{n+1}{\pi}\sum_x\sum_y f(x,y)V_{nm}^*(x,y), x^2+y^2 \leq 1 \tag{9}$$

A Zernike shape descriptor consists of low order magnitudes of Zernike moments. Table 1 shows the used Zernike moments magnitudes in this paper. Applying of ZM on a sample image is shown in figure 2.

Table 1. The List of Studied Zernike Moments in this paper

order(n)	Zernike Moments Amplitude	Number of oments	Total Feature
2	$\|Z_{2,0}\|;\|Z_{2,2}\|$	2	2
3	$\|Z_{3,1}\|;\|Z_{3,3}\|$	2	4
….	……	….	…
9	$\|Z_{9,1}\|;\|Z_{9,3}\|;\|Z_{9,5}\|;\|Z_{9,7}\|;\|Z_{9,9}\|$	5	28
10	$\|Z_{10,0}\|;\|Z_{10,2}\|;\|Z_{10,4}\|;\|Z_{10,6}\|;\|Z_{10,8}\|;\|Z_{10,10}\|$	6	34

Figure 2: the steps calculation of Zernike Moments (n=4, m=2) for a sample image. (a) Original Image (b) Complement Image. (c) Binary Image (**A=0.13734, φ=-96.5895**)

1.3. Gray low-level Co-occurrence Matrix (GLCM)

GLCM is a texture analysis technique for CBIR that has been introduced by Haralick and et al. [14]. The GLCM extracts texture information relevant to higher frequency components accurately. Co-occurrence matrices over an n×m image I for a certain offset $(\Delta x, \Delta y)$ are defined as:

$$C_{\Delta x,\Delta y}(i,j) = \sum_{p=1}^{n}\sum_{q=1}^{m}\begin{cases}1, & \text{if } I(p,q)=i \text{ and } I(p+\Delta x, q+\Delta y)=j \\ 0, & \text{otherwise}\end{cases} \tag{10}$$

where i and j are the image intensity values of the image, p and q are the spatial positions in the image I. Here, the offset $(\Delta x, \Delta y)$, is specifying the distance between the pixel-of-interest and its neighbor [25].Haralick and et al. are defined fourteen features for feature extraction. In this study four features namely energy, contrast, correlation and entropy are used for feature extraction in GLCM because they are not related [28], [29]. The features are given as follows respectively :

$$f_{Eng} = \sum_{i=0}^{L-1}\sum_{j=0}^{L-1} C(i,j) \tag{11}$$

$$f_{Con} = \sum_{n=0}^{L-1} n^2 \left\{ \sum_{i=0}^{L-1}\sum_{j=0}^{L-1} C(i,j) \right\} \tag{12}$$

$$f_{Cor} = \frac{\sum_{i=0}^{L-1}\sum_{j=0}^{L-1} ijC(i,j) - \mu_1\mu_2}{\sigma_1^2\sigma_2^2} \tag{13}$$

$$f_{Ent} = -\sum_{i=0}^{L-1}\sum_{j=0}^{L-1} C(i,j)\log C(i,j) \tag{14}$$

In order to make the texture features having rotation invariance, take offset parameters in four directions (0◦, 45◦, 90◦, 135◦) as GLCM. Finally we get the texture feature vector which has 16 components.

3. Image Retrieval System

3.1. Similarity Measure

After feature extraction of query image and database images, feature matching has to be done with a similarity metric. Following distance measures have been used for feature matching. Feature vector of query image can be denoted as $f_q=[f_1,f_2,\ldots,f_n]$. Similarly an n-dimensional feature vector

$f_{dbi}=[f_{i1},f_{i2},\ldots,f_{in}]$, $i=1,2,\ldots db$. is extracted for each image in the database and stored in the database. Four distance measures have been used for feature matching [30], in our experiments we used the d1 distance metric that is defined as:

$$d(q,DB)=\sum_i \left|\frac{f_i(q)-f_q(DB)}{v+f_i(q)+f_i(DB)}\right| \tag{15}$$

where the q and DB show the query and database images, v is any small number that avoids the denominator = 0. In all our experiments we consider v=1.

3.2 Combine three methods

The proposed CST system combines the HCH, ZM and GLCM features of image to reduce the similarity between q and DB. To determine the similarity of images using the fusing of color, shape and texture features (CST) system, the image matching according to d1 distance Δ^{CST} between q and DB is defined as:

$$d^{CST}(q,DB)=w_1\times d^{HCH}(q,DB)+w_2\times d^{ZM}(q,DB)+w_3\times d^{GLCM}(q,DB) \tag{16}$$

where w_1, w_2 and w_3 are the weights decided by the importance of each component for HCH, ZM and GLCM, respectively. Generally, Δ^{CST} decreases with the increase of similarity between q and DB.

3.3. Precision and Recall

Many evaluation measures have been used in content based image retrieval history [31]. Precision and recall commonly has been used to describe the performance of an image retrieval system [32]. For each database, every image is treated as query image and image retrieval process has been performed. For each query, the system responds to the L retrieved images with the minimal distance from the database image. The precision (P) and recall (R) of kth query image are defined as:

$$P(k)=\frac{n_k}{L} \quad \text{and} \quad R(k)=\frac{n_k}{N_d} \tag{17}$$

Where L is the number of retrieved images, n_k is the number of relevant images in the retrieved images and N_d is the number of all relevant images in the database.

4. Feature Selection

The main aim of feature selection is to select the best features that can not only achieve the maximum retrieval rate but can also simplify the calculation of image retrieval.

4.1. Ant Colony Optimization for feature selection (ACOFS)

In this section, we briefly review the ant colony optimization (ACO) algorithm. In the early 1990s, ACO was presented by Dorigo et al [33]. Each ant performs a simple task, but finally a colony's cooperative work can provide models for solving hard combinatorial optimization problems. The steps of ACOFS are as follows:

- **Feature extraction:** assume that M features as $F = (f_1,f_2,\ldots f_M)$ in each image are extracted from image database DB.
- **Fitness Functions:** in this section, the ants within the population initialization are denoted as a feature set. Then, match each ant to the respective feature; the value 0 for the ant means that the corresponding feature was not included in the calculation. Otherwise, the feature was included in the calculation.

Then, the image similarity distances between a query and image database are sorted descending. Therefore, for each query image, the image retrieval system responds to the first L retrieved images. If a similarity of query exists among the L retrieved image in database, the precision P(i) of ith query image is corrected, and P(i) =1. Otherwise, P(i) = 0. Therefore, the fitness function value can be derived by the precision P from Eq. (17), and then the average precision $\overline{P(i)}$ in i^{th} feature set of the all of the images is as follows:

$$\overline{P(i)} = \frac{1}{N_I}\sum_{i=1}^{N_I} p(i), \quad i = 1,2,\ldots, N_I \tag{18}$$

where N_I is the total image number. The optimum feature number M^* and the best precision $\overline{P^*(i)}$ of GAFS and PSOFS can be written by the following equation:

$$\overline{P^*(i)} = \max\{\overline{P(i)}\}, \qquad M^* = \arg\max\{\overline{P(i)}\} \tag{19}$$

- **Construction of feasible solutions**

to construct a solution each ant should start from the feature core. Next the ant randomly selects a feature, then selects the second feature from those unselected features with a given probability. That probability is calculated as follow [23]:

$$p_{ij}^k(t) = \frac{\tau_{ij}^{\alpha}\eta_{ij}^{\beta}(t)}{\sum_{l\in allowed_k}\tau\tau_{il}^{\alpha}\eta_{il}^{\beta}(t)}, \quad j \in allowed_k, \tag{20}$$

where k and t denote the number of ants and iterations, respectively, $allowed_k$ shows the set of conditional features that have not yet been selected, $\tau(i,j)$ and $\eta(i,j)$) are the pheromone value and heuristic information of choosing feature j when at feature i. In addition, $\alpha > 0$ and $\beta > 0$ are two parameters which determine the relative importance of the pheromone trail and heuristic information. If α is far larger than β, then ants will make decision mainly based on pheromone trails, and if β is far larger than α , ants will select those feature with higher heuristic information in a greedy manner**.**

- **Pheromone updating**

After each ant has constructed a solution, the pheromone on each updated as follow [24]:

$$\tau_{ij}(t+1) = \rho\tau_{ij}(t) + \Delta\tau_{ij}(t), \tag{21}$$

where $\tau(i,j)$ is the amount of pheromone at iteration t, $\tau_{ij}(t+1)$ is the amount of pheromone, ρ is a decay constant used to simulate the evaporation of pheromone, and $\Delta\tau_{ij}(i,j)$ is the amount of pheromone deposited, typically given by:

$$\Delta\tau_{ij}(t) = \begin{cases} \phi.\gamma(S^k(t)) + \dfrac{\varphi.(n - |S^k(t)|)}{n}, & \text{if } i \in S^k(t) \\ 0 & \text{otherwise} \end{cases} \tag{22}$$

where $S^k(t)$ is the feature subset found by ant k at iteration t, and $|S^k(t)|$ is its length. The pheromone is updated according to the measure of the retrieval performance. $\gamma(S^k(t))$ and feature subset length

ϕ and φ are two parameters that control the relative weight of classifier performance and feature subset length. In our work we assume $\phi = 0.4$ and $\varphi = 0.6$. The other Parameters of Ant Colony Optimization that used in simulations are given in table 3.

Table3: the Parameters of Ant Colony Optimization

Parameters	Value
Number of Ants	20
Maximum Iteration	25
α	1
β	0.8
τ	0.2
ρ	0.9

5. Simulation Results

The experiments results are compiled with MATLAB R2015a and a laptop with core i5 CPU and 4GB RAM in this paper**.**

5.1. Dataset

In This study we prepare a dataset consisting of 250 marine life images. The images are taken from 10 marine life species group in Persian Gulf and Oman sea and obtained mainly from Google image search and contributed by Iran Fisheries organization (IFO). Sample images from query set are shown in Figure 3. This 10 Classes are shown in Table 4.

Table 4: Ten classes of marine database

Class	Class Name
1	Cnidarian
2	Coral
3	Eagle ray
4	Echinoderms
5	Seashell
6	Marine reptiles
7	Sea grasses
8	Marine worm
9	Sea horses
10	Persian Gulf fishes

Figure 3: Marine database sample images query

5.2. Performance of image retrieval system

In this section, the performance of image retrieval using color, shape and texture features are presented. The experimental results of color moment in RGB and Lab color spaces and the HSV color histogram are shown in Table 5. Based on table 5, the HSV color histogram method has higher average precision retrieval than color moments and color moments in RGB color space provide better performance in comparison with Lab color space. A comparison results of all methods based on d1 distance for L = 15 retrieved images is given in Table 6. For higher retrieval performance we fuse the three color feature (HCH), shape feature (ZM) and texture feature (LBP) using Eq. (16). The results of combining three feature using Equation (16) are presented in Table 6. The weights of Equation (16) are: $w_1 = 0.9$, $w_2 = 0.8$ and $w_3 = 0.08$, that have been obtained through experiments using the similarity distance from image database. According to the results, the average precision of three HCH, ZM, GLCM are close to each other, but HCH has a little better accuracy. Fusion of three color, shape and texture features (CST) in compare with single features has the best retrieval result for the marine life image database (precision = 0.905).

Table 5: the comparison results of color features

	Retrieval Method		
	RGB color Moment	**Lab color Moment**	**HSV color Histogram**
Cnidarian	0.751	0.598	0.754
Coral	0.370	0.370	0.598
Eagle ray	0.479	0.391	0.479
Echinoderms	0.935	0.370	0.523
Seashell	0.823	0.527	0.980
Marine reptiles	0.370	0.370	0.754
Sea grasses	0.618	0.479	0.981
Marine worm	0.523	0.370	0.598
Sea horses	0.598	0.499	0.598
Persian Gulf fishes	0.754	0.980	0.618
Average	**0.622**	**0.496**	**0.688**

Table 6: The comparison results of between all features and fusion features

	Retrieval Method			
	HCH	**GLCM**	**ZM**	**CST**
Cnidarian	0.754	0.798	0.415	0.883
Coral	0.598	0.415	0.598	0.735
Eagle ray	0.479	0.863	0.671	0.936
Echinoderms	0.523	0.706	0.527	0.843
Seashell	0.980	0.443	0.827	1.000
Marine reptiles	0.754	0.370	0.598	0.868
Sea grasses	0.981	0.751	0.598	0.986
Marine worm	0.598	0.598	0.863	0.958
Sea horses	0.598	0.598	0.618	0.854
Persian Gulf fishes	0.618	0.751	0.980	0.991
Average	0.688	0.629	0.669	**0.905**

5.3. The performance of ACOFS

In this section, the performance of the ant colony Optimization feature selection (ACOFS) is evaluated. The experimental results from ACOFS for L= 15 retrieved images and comparison with all the studied methods are shown in Table 7**.** It is clear that the average precision of ACOFS is better than HCH, ZM and GLCM and the feature number of ACOFS is less than the feature numbers of HCH, ZM, GLCM and CST.

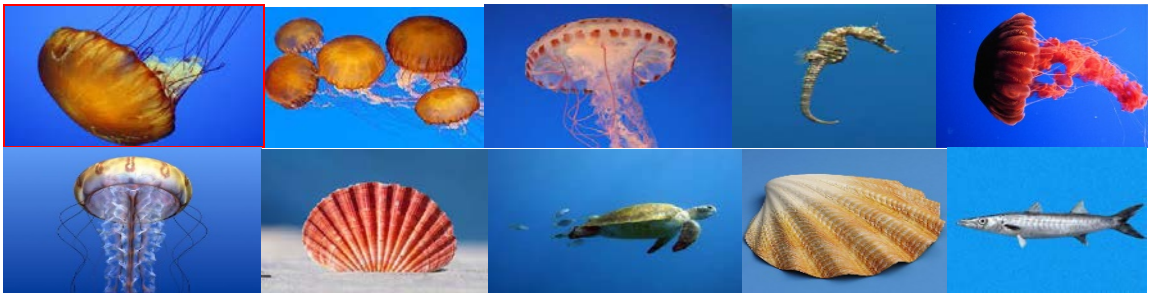
Table 7: The comparison results of ACOFS and all features

Retrieval Method	Feature Selection Method			
	Average performance		**ACOFS**	
	Feature Number	Average Precision	Feature Number	Average Precision
HCH	72	0.688	31.25	0.921
ZM	34	0.669	16.14	0.901
GLCM	16	0.629	11.4	0.911
HCH+ZM+GLCM=CST	122	0.905	**58**	**0.968**

Figure 4 demonstrate the retrieval results of a sample query image: #1 " Cnidarian " in marine life database. In these two figures, the left-upper image marked by a solid red line is a query (1st ranked image) and the other images are displayed in a raster scan order according to their retrieval ranks.

(a) Retrieval results of GLCM for image query # 1; 6 of 20 ground truth images found in the first 10 retrievals **(Precision=0.798)**..

(b) Retrieval results of Zernike Moments for image query # 1; 4 of 20 ground truth images found in the first 10 retrievals **(Precision=0.669)**.



(c) Retrieval results of HCH for image query # 1; 5 of 20 ground truth images found in the first 10 retrievals **(Precision=0.754)**.

(d) Retrieval results of CST for image query # 1; 8 of 20 ground truth images found in the first 10 retrievals **(Precision=0.905)**.

(e) Retrieval results of CST for image query # 1; all of 20 ground truth images found in the first 10 retrievals **(Precision=0.968**).

Figure 4: The retrieval results for image query #1

Conclusions

In this paper a scenario for using of CBIR in marine life images application was proposed. An image database specialized for the proposed scenario was prepared. Three content based image retrieval methods were applied to the databases. Performance evaluation of all the algorithms was compared based on the precision and recall evaluation measurement. in continue, the HCH of color , ZM of shape and GLCM of texture features are combined. an image retrieval method using multi-feature fusion is proposed. in addition, to achieve an acceptably high retrieval performance, the ACOFS is proposed. In our experiments regarding feature selections have shown that ACOFS can not only decrease the feature numbers, but also increase the retrieval average precision. Finally, it is found that HSV color space is the best color space for our prepared tourism database especially in applying color features CBIR algorithms. Furthermre, among all the algorithms, HSV color histogram had the best retrieval performance.

References

[1] A. Alzu'bi, A. Amira, and N. Ramzan, "Semantic content-based image retrieval: A comprehensive study," J. Vis. Commun. Image Represent., vol. 32, pp. 20–54, 2015.

[2] Z. Raisi, F. Mohanna, and M. Rezaei, "Content-Based Image Retrieval for Tourism Application Using Handheld Devices'','' IJICTR J., 2011.

[3] Z. Zeng, "A novel local structure descriptor for color image retrieval," Inf., vol. 7, no. 1, pp. 1–14, 2016.

[4] M. Zhao, H. Zhang, and J. Sun, "A novel image retrieval method based on multi-trend structure descriptor," J. Vis. Commun. Image Represent., vol. 38, pp. 73–81, 2016.

[5] D. Zhang, M. M. Islam, and G. Lu, "A review on automatic image annotation techniques," Pattern Recognit., vol. 45, no. 1, pp. 346–362, 2012.

[6] X.-Y. Wang, L.-L. Liang, W.-Y. Li, D.-M. Li, and H.-Y. Yang, "A new SVM-based relevance feedback image retrieval using probabilistic feature and weighted kernel function," J. Vis. Commun. Image Represent., vol. 38, pp. 256–275, Jul. 2016.

[7] M. M. Mohammed, A. Badr, and M. B. Abdelhalim, "Image classification and retrieval using optimized Pulse-Coupled Neural Network," Expert Syst. Appl., vol. 42, no. 11, pp. 4927–4936, 2015.

[8] G. A. Montazer and D. Giveki, "Content based image retrieval system using clustered scale invariant feature transforms," Opt. - Int. J. Light Electron Opt., vol. 126, no. 18, pp. 1695–1699, 2015.

[9] C. H. Lin, D. C. Huang, Y. K. Chan, K. H. Chen, and Y. J. Chang, "Fast color-spatial feature based image retrieval methods," Expert Syst. Appl., vol. 38, no. 9, pp. 11412–11420, 2011.

[10] S. S. Hiwale and D. Dhotre, "Content-based image retrieval: Concept and current practices," in 2015 International Conference on Electrical, Electronics, Signals, Communication and Optimization (EESCO), 2015, pp. 1–6.

[11] J.-M. Guo, H. Prasetyo, H. Lee, and C.-C. Yao, "Image retrieval using indexed histogram of Void-and-Cluster Block Truncation Coding," Signal Processing, vol. 123, pp. 143–156, Jun. 2016.

[12] M. Xiao, J. Lu, and G. Xie, “A Novel Optimization-Based Approach for Content-Based Image Retrieval,” Appl. Mat hemat ics, vol. 2013, 2013.

[13] Z. Raisi, F. Mohanna, and M. Rezaei, “Applying Content-Based Image Retrieval Techniques to Provide New Services for Tourism Industry,” Int. J. Adv. Netw. Appl., vol. 6, no. 2, pp. 2222–2232, 2014.

[14] R. M. Haralick, K. Shanmugam, and I. Dinstein, “Textural Features for Image Classification,” IEEE Trans. Syst. Man. Cybern., vol. 3, no. 6, pp. 610–621, Nov. 1973.

[15] Z. M. Ma, G. Zhang, and L. Yan, “Shape feature descriptor using modified Zernike moments,” Pattern Anal. Appl., vol. 14, no. 1, pp. 9–22, Feb. 2011.

[16] P. Shanmugavadivu, P. Sumathy, and A. Vadivel, “FOSIR: Fuzzy-Object-Shape for Image Retrieval applications,” Neurocomputing, vol. 171, pp. 719–735, 2016.

[17] M. Huang, Y. Ma, and Q. Gong, “Image Recognition Using Modified Zernike Moments,” Sensors & Transducers, vol. 166, no. 3, pp. 219–223, 2014.

[18] H. Zhang and G. Sun, “Feature selection using tabu search method,” Pattern Recognit., 2002.

[19] S. Lin, Z. Lee, S. Chen, and T. Tseng, “Parameter determination of support vector machine and feature selection using simulated annealing approach,” Appl. Soft Comput., 2008.

[20] C.-H. Lin, H.-Y. Chen, and Y.-S. Wu, “Study of image retrieval and classification based on adaptive features using genetic algorithm feature selection,” Expert Syst. Appl., vol. 41, no. 15, pp. 6611–6621, 2014.

[21] R. Sharkawy, K. Ibrahim, and M. Salama, “Particle swarm optimization feature selection for the classification of conducting particles in transformer oil,” IEEE Trans., 2011.

[22] M. Deriche, “Feature Selection using Ant Colony Optimization,” 2009 6th Int. MultiConference Syst. Signals Devices, vol. 36, no. 4, pp. 6843–6853, 2009.

[23] Y. Chen, D. Miao, and R. Wang, “A rough set approach to feature selection based on ant colony optimization,” Pattern Recognit. Lett., vol. 31, no. 3, pp. 226–233, 2010.

[24] M. H. Aghdam, N. Ghasem-Aghaee, and M. E. Basiri, “Text feature selection using ant colony optimization,” Expert Syst. Appl., vol. 36, no. 3 PART 2, pp. 6843–6853, 2009.

[25] A. Malisia and H. Tizhoosh, “Image thresholding using ant colony optimization,” Comput. Robot Vis. (CRV’06 …, 2006.

[26] B. Mohan and R. Baskaran, “A survey: Ant Colony Optimization based recent research and implementation on several engineering domain,” Expert Syst. Appl., 2012.

[27] J. Tian, W. Yu, and S. Xie, “An ant colony optimization algorithm for image edge detection,” 2008 IEEE Congr. Evol., 2008.

[28] M. Huang, H. Shu, Y. Ma, and Q. Gong, “Content-based image retrieval technology using multi-feature fusion,” Opt. - Int. J. Light Electron Opt., vol. 126, no. 19, pp. 2144–2148, Oct. 2015.

[29] G.-H. Liu and J.-Y. Yang, “Image retrieval based on the texton co-occurrence matrix,” Pattern Recognit., vol. 41, no. 12, pp. 3521–3527, 2008.

[30] Y. R. Charles, R. Ramraj, J.-M. Guo, H. Prasetyo, H. Lee, C.-C. Yao, S. Pandey, P. Khanna, H. Yokota, X. Y. Li, M. Liu, L. Yang, Y. Liang, M. Zhao, H. Zhang, J. Sun, S. Patil, S. Talbar, G. Ali, D. Giveki, I. Retrieval, U. Color, and R. M. Hawlick, “A novel image retrieval method based on multi-trend structure descriptor,” J. Vis. Commun. Image Represent., vol. 126, no. VOL. 1, pp. 47–54, Jun. 2016.

[31] J. Smith, “Image retrieval evaluation,” Content-Based Access Image Video Libr., 1998.

[32] B. M. Mehtre, M. S. Kankanhalli, and W. F. Lee, “Shape measures for content based image retrieval: A comparison,” Inf. Process. Manag., vol. 33, no. 3, pp. 319–337, May 1997.

[33] T. R. Iridia, M. Dorigo, U. L. De Bruxelles, A. F. Roosevelt, and L. M. Gambardella, “Ant colonies for the traveling salesman problem,” pp. 1–10, 1996.

[34] SMR. Hashemi, M. Kalantari, and M. Zangian, "Giving a New Method for Face Recognition Using Neural Networks.", International Journal of Mechatronics, Electrical and Computer Technology Vol. 4(11), A pr, 2014, pp. 744-761, ISSN: 2305-0543

[35] SMR. Hashemi, A. Broumandnia, " A New Method for Image Resizing Algorithm via Object Detection ." International Journal of Mechatronics, Electrical and Computer Technology, Vol 5, Issue 16 2015.

[36] SMR. Hashemi, S. Mohammadalipour and A. Broumandnia, " Evaluation and classification new algorithms in Image Resizing.", International Journal of Mechatronics, Electrical and Computer Technology Vol. 5(18) Special Issue, Dec. 2015, PP. 2649-2654, ISSN: 2305-0543

[37] SMR. Hashemi, M. Faridpoor " Evaluation of the Algorithms of Face Identification" IEEE-2015, 2nd International Conference on Knowledge-Based Engineering and Innovation (KBEI).

[38] SMR.Hashemi, M. Hajighorbani, Mohammad Mahdi Deramgozin and B. Minaei-Bidgoli, " Evaluation of the Algorithms of Face Identification ", International Journal of Mechatronics, Electrical and Computer Technology, Vol. 6(19), Jan. 2016

[39] SMR.Hashemi, Mohammad Mahdi Deramgozin, M.Hajighorbani and Ali Broumandnia, " Methods of Image Re-targeting Algorithm Using Markov Random Field ", International Journal of Mechatronics, Electrical and Computer Technology Vol. 6(20), Apr. to Jul., 2016

Authors

Zobeir Raisi received his B.Sc. degree in electronic engineering from University of Sistan and Baluchestan in 2009 and his M.Sc. degree in communication engineering (with honor) from University of Sistan and Baluchestan, Zahedan, Iran in 2011. He is currently a faculty member in Chabahar Maritime University. And member of the Computer Vision and Image Processing, IAEE and Iranian Fuzzy System Committees. His current research interests include pattern recognition, image processing, image retrieval, computer vision and digital signal processing (DSP).

Javad Azarakhsh received his B.Sc. degree in electronic engineering from University of Sistan and Baluchestan in 2008 and his M.Sc. degree in power system analysis from University of Semnan, Semnan, Iran in 2012. He is now the head of Electrical engineering department in Chabahar Maritime University, Chabahar, Iran. His research areas are power quality analysis, intelligent systems and signal processing etc.