Proceedings of the World Congress on Engineering 2013 Vol II,
WCE 2013, July 3 - 5, 2013, London, U.K.

A Meta-Heuristic Optimization Approach for Content Based Image Retrieval using Relevance Feedback Method

[1]T.Kanimozhi, [2]K.Latha

***Abstract* - With the potential growth of multimedia hardware and applications, the machines have to realize the information by adapting to the internal information. An adaptive content based image retrieval (CBIR) approach based on relevance feedback and Firefly algorithm is proposed in this paper. In addition to the color descriptor, wavelet-based texture descriptor is considered to improve the retrieval performance. Feature extraction has been done with the Euclidean distance estimation between the pixels; relevance feedback (RF) based approach but all concerns with the extraction of image accuracy. This research work has a focused approach to increase the performance by optimizing image feature by adopting with the firefly algorithm (FA). The experimental results compared with the other optimization algorithms like particle swarm optimization and genetic algorithm demonstrate the feasibility of the approach.**

***Index Terms* — Content-based image retrieval, Relevance Feedback, Firefly Algorithm, color descriptor, texture descriptor.**

I. INTRODUCTION

With the huge requirements of multimedia information processing to process the real-time information in terms of visual objects in many practical applications, multimedia information retrieval becomes essential, among which image retrieval has becoming widely recognized. Moreover, it is also desirable to develop image retrieval tools to browse and search images effectively and efficiently because of the explosive growth of personal image records and image records on the Internet. To give text annotations [1], [2] to all images manually is tedious and impractical. In addition, automatic image annotation [3] is generally beyond current techniques.

Therefore, content-based image retrieval [4]-[6] has gained much attention in the past decades. CBIR is a technique to retrieve images from an image database such that the retrieved images are semantically relevant to a query image provided by a user.

Initially, the research activities in CBIR primarily focused on representing images by using low-level visual features, which can be automatically extracted from images, to reflect the color, texture and shape information of the image.

Manuscript received 18 Mar. 2013; revised 08 Apr. 2013;

1. T.Kanimozhi, is a Research Scholar, Dept. of Computer Science & Engg, Anna University Chennai, University College of Engg., BIT Campus, Tiruchirappalli, Tamilnadu, India.(e-mail : csrkani@gmail.com)

2. Dr.K.Latha, Assiatant Professor, .Dept. of Computer Science & Engg, Anna University Chennai, University College of Engg., BIT Campus, Tiruchirappalli, Tamilnadu, India. (e-mail: erklatha@gmail.com)

However the retrieval performance is still far from satisfactory.

Relevance feedback (RF) has been demonstrated to be a powerful tool which involves the user in the loop to enhance the performance of CBIR. Popular RF schemes can exhibit some general limitations of over sensitivity to subjective labeling by users and the inability to accumulate knowledge over different sessions and users.

RF approaches also having the critical issues that yet to be unsolved. This would be occurred because of the user interaction leads to a time consuming, not getting the relevant information in a quick convergence. This is being focused for a new image without positive examples are available for the successful retrieval. During the retrieval process, if it converges to very sub optimal local solution and if we could not able to explore the image space that creates critical issues. This problem depends on the size of the databases.

To encounter the above two issues in relevance feedback of the image retrieval system, we considered the speculative and effective design in which the RF technique is integrated into meta-heuristics firefly. Recently, a new modern meta-heuristic algorithm, called firefly algorithm, developed by Xin-she Yang [7], [8] is a population based technique. This algorithm mimics some of the characteristics of firefly swarms and their flashing behavior. A firefly with lower flash intensity tends to be attracted towards other fireflies with higher flash intensity in which the light intensity decreases as the distance increases [9]. In this paper, the firefly optimizer has been chosen as an effective image space exploration and an optimization engine that would solve the convergence to the maximum level. All the works are progressed through color and texture features.

The rest of the paper is organized as follows: Section II briefly review the related works about CBIR and firefly algorithm. Section III presents the proposed approach. Experimental results are presented and analyzed in Section IV. Finally, we conclude and discuss future research directions in Section V.

II. RELATED WORKS

A. CBIR and Relevance Feedback

There are some literatures that overview and compare the feature extraction techniques in CBIR [10], [11]. Also, there are some papers on CBIR that adopts the color descriptor. Neetu Sharma et al [12] investigated the two different methods for describing the content of images which are global descriptor attributes and color histogram approach for

ISBN: 978-988-19252-8-2
ISSN: 2078-0958 (Print); ISSN: 2078-0966 (Online)

efficient image retrieval. Authors in [13] extended the EM-variant algorithm to estimate the parameters of the Gaussians in order to detect an object in color image retrieval systems. Authors in [14] proposed a technique which uses the back-projection of color sets for automated extraction of local color regions and representation of color content, thereby provided an efficient indexing and effective color image retrieval. Zhenhua Zhang et al [15] proposed a technique for improving the representation of color histogram by adopting a non-uniform quantization and segmentation algorithm in segmentation based image retrieval. Ching-Hung Su et al [16] proposed a scheme that transfers each image into quantized color code and then compared with the database for efficient image retrieval.

Texture is also an important image feature that plays a major role in human visual perception [17]-[18]. Combination of color and texture features is also an important property in CBIR systems [19]-[20].

In order to have wide acceptance, recent approaches include human-computer interaction perspective [23]-[27] as well as in CBIR. C. Y. Li et al [28] developed a unified graph theoretic approach for relevance feedback and image matching in region level and improved the retrieval performance. Dewen Zhuang et al [29] segmented the image into main region and margin region based on high dimension biomimetic information geometry theory and then integrated with relevance feedback, thereby improved the retrieval efficiency. T. S. Huang et al [30] discussed about various algorithm for interactive multimedia retrieval. In [31], the author presented a new notion of fuzzy relevance feedback and the corresponding fuzzy radial basis function network (FRBFN) -based framework into the interactive CBIR systems based on soft decision. Y. Rui et al [32] adopted feature re-weighting for relevance feedback into CBIR systems and improved their performance. Y. Rui et al [33] adopted optimal learning over heuristic-based feature weighting for relevance feedback into CBIR systems and improved their performance.

B. Firefly Optimization

One of the excellent optimization algorithms is invented by a search heuristic engine that mimics the process of natural evolution. We found some of the literature survey related to this algorithm with optimization of images.

Yudong Zhang et al [34] [35] discussed about the image registration mechanism using a novel approach. The Image registration has been modeled with normal cross correlation model as optimization suite. In [38], the authors proposed, presented and tested the firefly algorithm to optimize the economic emission load dispatch problem so as to minimize both the fuel cost and emission of generating units. Herbert M. Gomes [39] proposed a methodology based on firefly metaheuristic algorithm and performed a structural mass optimization on shape and size by taking highly non-linear dynamic problems with several constraints. Olympia Roeva [40] adapts FA for a model parameter identification of an E-coli fed-batch cultivation process and performs parameter optimization. N. Chai-ead et al. [41] adapts bees and firefly algorithm for solving noisy non-linear optimization problems. In [42], FA is applied to solve job shop scheduling problem which involves complex combinatorial optimization that are categorized into non-deterministic polynomial (NP) hard problem.

Some of the papers that are related to image retrieval are presented below. Xu Zhang et al [44] discussed about the image retrieval optimization with PSO with r-selection and k-selection of Ecology. He proved r/k PSO with positive and negative feedback samples to enhance the image retrieval by changing the weights based on the user input. Chin-Chin Lai et al [45], [46] proved the reduction of semantic gap between high level sample features and low level sample features to reach the intended image by Genetic Algorithm as an optimizer.

III. PROPOSED SYSTEM

A. Distance Calculation

The image is defined as the set of combination of color information, texture and shape of the object in the image.

Let K be the image, it is defined by

K = {color, shape, texture}

Among these features, color and texture features are considered in this paper. The first and foremost step is to represent the images in terms of features. The visual signature of the ith image is made up of different feature vectors, composed by: M_{ch} color histogram bins c_i^{ch}, M_{cm} color moments c_i^{cm}, M_{edh} edge direction histogram c_i^{edh} and Mwt wavelet texture feature values c_i^{wt}. The feature vector $c_i = [c_i^{ch} + c_i^{cm} + c_i^{edh} + c_i^{wt}]$ of dimension D= M_{ch} + M_{cm} + M_{edh}+ M_{wt} provides the overall description of the image. The feature vectors of query image are computed online and the feature vectors of stored database images are computed offline. From there, each image is represented as feature vector in D-dimensional space. After the mapping of query image and stored database image into its feature vector, the system shows the most M_{FB} nearest images to the user from the entire database, based on weighted Euclidean distance between feature vector pairs.

Mathematically expressed as

$$\begin{aligned} Dist(c_q; c_s) = {} & WMSE(c_q^{ch}; c_s^{ch}) \\ & + WMSE(c_q^{cm}; c_s^{cm}) \\ & + WMSE(c_q^{edh}; c_s^{edh}) \\ & + WMSE(c_q^{wt}; c_s^{wt}) \end{aligned} \quad (1)$$

where c_q is the query feature vectors and c_s is the stored database feature vectors; s=1,…., M_{DB} , where M_{DB} is the total number of database images. *WMSE* is the weighted Euclidean distance calculated between a pair of feature vectors:

$$WMSE(c_q; c_s) = \frac{1}{N} \sum_{j=1}^{N} (c_{qj} - c_{sj})^2 w_j^k \quad (2)$$

where w_j^k is a vector of weights associated to the features at kth iteration and N is equal to M_{ch} or M_{cm} or M_{edh} or

ISBN: 978-988-19252-8-2
ISSN: 2078-0958 (Print); ISSN: 2078-0966 (Online)

M_{wt}. At first iteration, w_j^k =1; j=1… N; that is all the features are equally important.
The idea is to compare the pixel intensity and value of the input image to the stored database.
Let's Assume query image or input image as Q(I) and stored image as S(I).

$$F(x)=\begin{cases}0 & \text{if } Q(I)=S(I)\\ -1 & \text{if } Q(I)\neq S(I)\end{cases} \quad (3)$$

Where Q(I) = $Q_i(I) * C_i$
S(I) = $S_j(I) * C_j$

i, j are the index prefixes of the pixel.
Q (I) and S (I) are the reference and input image.
F(x) is the system function it validates the pixel equivalence of the image.
From the above relation the spatial transformation image matrix T* is given by

$$T^{*}=E(Q(I),S(I)) \quad (4)$$

E is the similarity measurement of the image.
The cross correlation between the two images is given by

$$C(Q,S)=\frac{1}{N}\sum_{(i,j)}\frac{(Q-\mu_q)(S-\mu_s)}{(\sigma_q\sigma_s)} \quad (5)$$

where C(Q,S) is the cross correlation of pixels in the image.
Transformation Matrix T* is given by substitute (5) in (4)

$$C(Q,S)=E\left\{\frac{1}{N}\sum_{(i,j)}\frac{(Q-\mu_q)(S-\mu_s)}{(\sigma_q\sigma_s)}\right\} \quad (6)$$

After computing the minimum distance, the system ranks the entire database and sort the results. Then the M_{FB} nearest image is shown to the user for collecting the first feedback. The user tags the images as relevant and irrelevant according to their mental view of query. Now the two image subsets as relevant and irrelevant are created and updated during all the iterations.

B. Feature Reweighting

The goal of weight updating is to emphasize the most important ones for the significant number of samples which is classified by the user as M_{FB} relevant and irrelevant images. The feature re-weighting algorithm used is based on a set of statistical characteristics [22]. In practice, taking into account of the user feedback, a dynamic feature selection is performed. Based on the concept of dominant range and confusion set, it is feasible to calculate the discriminant ratio δ_f^k on the f[th] feature (f = 1,2,…..,D) at the k[th] iteration which shows the ability of this feature to separate irrelevant images from relevant ones. The updated weight is then computed as follows

$$w_f^{k+1}=\frac{\delta_f^k}{\sigma_f^{k,R}} \quad (7)$$

where $\sigma_f^{k,R}$ is the standard deviation of f[th] feature of the relevant image subset at the k[th] iteration which is modified[43] with normalization factor, thereby it limits the maximum weight to 1.

C. Firefly Algorithm Modeling

Firefly Algorithm (FA) is a nature-inspired algorithm which is based on the flashing behaviors of the firefly swarm. The development of firefly inspired algorithm consists of three idealized rules [9]. (1) Artificial fireflies are unisex so that one firefly is attracted to other fireflies regardless of their sex; (2) the degree of the attractiveness is proportional to their brightness of light intensity and they both decreases as the distance due to the fact that the air absorbs light. Thus for any two flashing fireflies, the less bright one will move towards the brighter one. If there is no brighter one than a particular firefly, it will move randomly; (3) the brightness of flashing light is determined by the value of objective function which is to be optimized.

In this paper the retrieval problem is modeled as an optimization process. To this purpose, the swarm of agents A_n or swarm of fireflies are defined as points and are randomly distributed inside the feature space i.e., D-dimensional vectors in the search space.

The decision variables of firefly algorithm are the four feature vectors as M_{ch} , M_{cm} , M_{edh} and M_{wt}. The brightness of light intensity is associated with the objective function which is related to the sum of weighted Euclidean distance between the query image and the stored database image in D-dimensional search space.

Based on this objective function, initially all the fireflies are randomly deployed across the solution space. There are two phases of firefly algorithm which are described as follows [9]:

i. Light intensity variation

The color and texture feature values are related to the objective values, so for a maximization/minimization problem, a firefly with higher intensity will attract another firefly with higher probability, and vice versa. Given that there exists an n number of swarm of fireflies with $M_{FB} \leq n < M$ in which each firefly is determined by the light intensity and x_i represents a solution for a firefly i, whereas $f(x_i)$ denotes its corresponding objective function. Here the color and texture feature values of an image I of a firefly is equivalent to the value of objective function

$$I_i = f(x_i) \qquad 1 \leq i \leq n \quad (8)$$

ii. Movement towards attractive fireflies

The attractiveness β of the firefly is proportional to the light intensity received by the adjacent fireflies. Suppose β_0 is the attractiveness with distance r = 0, so for two fireflies i and j at locations x_i and x_j, their attractiveness is calculated as

$$\beta_r(i,j)=\beta_0 e^{(-\gamma r(i,j)^2)} \quad (9)$$

$$r(i,j)=|x_i-x_j| \quad (10)$$

where r(i, j) denotes the distance between fireflies i and j, γ denotes the light absorption coefficient. Suppose firefly j is brighter than firefly I of the input image, then firefly i will move to a new location as

$$x_i(t+1)=x_i(t)+\beta_0 e^{(-\gamma r^2)}(x_j-x_i) \quad (11)$$

ISBN: 978-988-19252-8-2
ISSN: 2078-0958 (Print); ISSN: 2078-0966 (Online)

When the value of r (distance between two fireflies) is small/large, the firefly will move a large/small distance which will affect the computation time of this algorithm. As the swarm of agent i moves towards the swarm of agent j, the position of agent i is changed from binary number to a real number. So this real number must be replaced by binary number. The following sigmoid function restricts the interval to be zero to one [37].

$$S(x_{ih}) = \frac{1}{1+e^{-x_{ih}}} \tag{12}$$

where $S(x_{ih})$ denotes the probability of bit x_{ih} taking 1.

The most important point in an optimization process is to define the target function that is to be minimized or maximized which is said to be fitness. The fitness value shows the effectiveness of position reached by the swarm of agent. Taking into account of irrelevant and relevant images, the weight cost function [43] defined by Eq.13 expresses the fitness associated to the solution space found by the swarm of fireflies.

$$\phi^k(A_n) = \frac{1}{N_{rel}^k}\sum_{r=1}^{N_{rel}} Dist(A_n^k; x_r^k) + \frac{1}{\frac{1}{N_{irr}^k}\sum_{r=1}^{N_{irr}} Dist(A_n^k; x_i^k)} \tag{13}$$

where x_i^k ; i = 1,…, N_{irr}^k and x_r^k ; r = 1,…, N_{rel}^k are the images in the irrelevant and relevant image subsets, respectively. The computation of Dist(.) is same as calculated at the previous step. The lower the fitness value, better the positions reached by the firefly which is nearest to the relevant images and far from irrelevant images. Based on the fitness value, it is possible for the fireflies to re-order to get new ranking. Thus based on swarm intelligence, the FA finds the global optima of objective function by investigating the foraging behavior of fireflies.

It is worth noting that it is possible to view the swarm agents as query points that will explore the D-dimensional search space, which is made of image features (f = 1,2,…..,D)with its light intensity. After the two phase of firefly algorithm at first iteration, updating process is done consequently at further iteration. The value of objective function, attractiveness and movement of firefly towards other firefly are recalculated according to (8), (9) and (11) respectively where new relevant images are chosen by the user. Thereby the firefly moves towards the new area in the feature space where the new relevant images may be found, after every user feedback.

In fact, the swarm agent moves in a continuous fashion inside the solution space, while the images of the database are in discrete and fixed set of points. Hence, further operation is needed to complete a single iteration. The first swarm agents ranked according to (13) are placed at "correct position" in the solution space, which is to be associated to the nearest images in the database according to (1). Thus a new set of images are obtained which is then shown to the user. If the swarm of fireflies points to the irrelevant image which is already classified or more than one swarm of firefly points to the same image, those images are discarded and the next nearest images are considered until different M_{FB} set of images are collected by the user. After the user feedback, the process of feature re-weighting and firefly updating is iterated. The above process ends, when the user verifies one of the following conditions: 1) the result of search satisfies user 2) the relevant number of images targeted are achieved or 3) when it reaches predefined number of iteration. All the relevant images are presented to the user, after the process ends.

IV. Experimental Results

A. Experimental Setup

In our experiments, we used the Corel database covering a wide range of semantic categories from natural scenes to artificial objects. The dataset is partitioned into 10 categories, including Butterfly, buildings, hills, flowers, earth, sky, trees, boats, birds, statue, horses, and elephants, etc., and each category is represented by 250 images, for a total of 2500 images. All the experiments were implemented in Matlab, running on a personal computer with Intel Dual Core 3GHZ processor and 4 GB RAM. To analyze the effectiveness of our proposed approach precision, recall, F-Measure, true positive and false positive are used to measure the related experimental evaluations.

B. Visual Signature

As usual, the computation of the feature vector is online for the query image and offline for the database image. The feature vectors of database images are stored in a database for run time access. The visual signature of each image is composed of four different feature vectors. The first one is 32-bin color histogram calculated in the HSV color space, the second one is 9-bin color moments [21] extracted from HSV color space, the third one is 8-bin edge direction histogram [22] is obtained from the edge map of an image and the forth one is 18-wavelet texture energy values [48].

The sum of all these 67- dimensional feature vectors is used to describe an overall image.

C. Parameter setting

The swarm of fireflies is randomly initialized in the solution space. The parameter values used in this paper are

Number of fireflies (F) =18
Light absorption co-efficient (γ) =1
Attractiveness (β) =1
Number of generation (I) = 110

The same parameter values are suggested by Yang X. S. [47] for most of the applications. After the fireflies are randomly distributed in the feature space, the parameter value of β strongly determines the firefly positions which are neighborhood to the brightest firefly. This is equivalent to the co-operative local search scheme. The value of light absorption co-efficient γ=1 determines the value of light intensity as the distance increases from the communicated firefly which results in the complete random search.

The number of function evaluation [36] computed in the firefly algorithm can be found as follows: Let F be the initial population size and I be the maximum number of generation. Then, the number of function evaluations for each iteration is $\frac{F(F-1)}{2}$ and the total number of function

ISBN: 978-988-19252-8-2
ISSN: 2078-0958 (Print); ISSN: 2078-0966 (Online)

evaluations is $\frac{F(F-1)}{2} * I$. In this paper, the maximum number of generation used is 110. Therefore, in one simulation run, the number of function evaluation (with F=18 and I=110) generated is 16830. The results of the proposed approach and the comparison results are tabulated. Thus, it is inferred from the Table II, III, IV the proposed method shows higher performance when compare to PSO and GA.

Table I. Retrieval precision values of the proposed approach

Precision values								
Iteration / Category	#1	#2	#3	#4	#5	#6	#7	#8
Butterfly	6.86	46.69	51.82	53.17	65.85	69.33	79.09	97.43
Building	7.49	31.92	32.41	40.38	68.37	69.95	91.16	98.18
Hills	7.11	39.45	40.34	44.5	48.32	49.3	56.84	78.12
Flowers	6.6	21.26	29.34	32.8	57.08	62.21	74.3	90.25
Earth	7.33	20.62	28.21	77.303	79.83	80.28	92.44	91.42
Sky	7.17	36.68	58.07	62.77	70.04	73.16	85.6	98.56
Tree	6.509	12.01	32.29	42.8	45.88	55.92	54.99	90.17
Boat	7.36	29.56	34.34	41.72	61.2	66.05	92.47	94.902
Bird	7.52	11.31	23.78	30.26	40.86	69.66	91.28	99.42
Statue	6.93	23.9	42.21	60.69	60.25	64.01	68.67	74.91

Table II. Average performance of GA+RF Image retrieval

GA+RF					
Category	P(%)	R(%)	F_1(%)	Tp(%)	Fp(%)
Butterfly	78.27	58.66	33.07	25.22	57.17
Buildings	27.66	25.93	12.88	36.88	98.63
Hills	78.57	21.90	16.46	29.87	69.85
Flowers	78.97	62.21	34.21	23.14	44.59
Earth	78.87	80.53	39.27	56.61	6.69
Sky	78.37	80.27	39.20	62.13	79.28
Tree	78.57	53.84	51.45	67.97	19.18
Boat	27.96	67.50	19.03	25.83	67.34
Bird	78.07	91.43	41.75	31.59	20.63
Statue	78.17	10.38	9.93	51.21	26.65

Table III. Average performance of PSO+RF

PSO+RF					
Category	P(%)	R(%)	F_1(%)	Tp(%)	Fp(%)
Butterfly	79.10	16.21	12.73	80.80	5.2
Buildings	78.49	37.76	24.93	92.91	30.97
Hills	75.60	78.09	37.67	46.26	27.42
Flowers	78.75	56.05	32.23	93.96	36.93
Earth	76.75	11.69	9.36	53.81	49.94
Sky	59.54	11.59	8.96	65.04	50.47
Tree	79.11	95.56	42.77	0.63	35.77
Boat	78.79	78.46	38.81	64.83	64.53
Bird	79.11	2.23	1.21	67.34	99.79
Statue	67.2	4.23	3.08	92.76	40.52

Table IV. Average performance of proposed method

Proposed approach					
Category	P(%)	R(%)	F_1 (%)	Tp(%)	Fp(%)
Butterfly	90.83	0.28	0.560	99.81	0.057
Buildings	95.39	0.02	0.041	99.97	0.057
Hills	93.61	0.63	1.251	99.47	0.055
Flowers	91.63	0.66	1.312	99.43	0.055
Earth	99.73	0.73	1.449	99.37	0.056
Sky	94.27	1.25	2.466	98.85	0.055
Tree	95.92	100	96.86	98.85	0.056
Boat	92.26	0.15	0.31	99.84	0.055
Bird	98.95	0.60	1.206	99.49	0.056
Statue	96.57	0.73	1.44	99.37	0.056

V. CONCLUSION AND FUTURE WORK

This paper has presented the Firefly based content based image retrieval optimization. The CBIR system has been implemented with the relevance feedback mechanism and for the optimization the objective function for the firefly has been designed with image color parameters and texture parameters. According to the performance with respect to the image precision, firefly has a deeper precision accuracy than the PSO and GA method optimization. Hence, it is highly efficient, robust and highly rapid for image accuracy based application.

The future research work focuses on improving the retrieval quality by using region based image retrieval and Indexing technique based on the FATT structure. User's query log data can be integrated into the proposed work to further increase the retrieval quality. This proposed work can also be used for other multimedia retrieval or multimedia recommendation.

REFERENCES

[1] V.S. Tseng, J.H. Su, J.H. Huang, and C.J. Chen, "Integrated Mining of Visual Features, Speech Features and Frequent Patterns for Semantic Video Annotation," *IEEE Trans. Multimedia*, vol. 10, no. 2, pp. 260-267, Feb. 2008.

[2] V.S. Tseng, J.H. Su, B.W. Wang, and Y.M. Lin, "Web Image Annotation by Fusing Visual Features and Textual Information," *Proc. 22nd ACM Symp. Applied Computing*, Mar. 2007.

[3] J. Jeon, V. Lavrenko, and R. Manmatha, "Automatic Image Annotation and Retrieval Using Cross-Media Relevance Models," *Proc. 26th Annual International ACM SIGIR Conf.,* pp. 119-126, 2003.

[4] Datta, R., Joshi, D., Li, J., and Wang, J. Z. 2008. Image retrieval: Ideas, influences, and trends of the new age. *ACM Comput. Surv.* 40, 2, Article 5 (April 2008), 60 pages DOI = 10.1145/1348246.1348248.

[5] Nidhi Singhai, Prof. Shishir K. Shandilya, "A Survey On: Content Based Image Retrieval Systems," *International Journal of Computer Applications* (0975 – 8887) Volume 4 – No.2, pp. 22-26, July 2010.

[6] A. W. Smeulders, M.Worring, S. Santini, A. Gupta, and R. Jain, "Content- based image retrieval at the end of the early years," *IEEE Trans. Pattern Anal. Mach. Intell.,* vol. 22, no. 12, pp. 1349–1380, Dec. 2000.

[7] Yang, X. S., (2010) "Firefly Algorithm, Stochastic Test Functions and Design Optimization", *Int. J. Bio-Inspired Computation*, vol. 2, no. 2, pp. 78–84, Mar 2010.

[8] Yang X. S, (2009)"Firefly algorithms for multimodal optimization", in: Stochastic Algorithms: Foundations and Applications, SAGA 2009, *Lecture Notes in Computer Sciences,* Vol. 5792, pp. 169-178.

[9] Yang X. S. "Multiobjective firefly algorithm for continuous optimization", *Engineering with computers Systems*, DOI 10.1007/s00366-012-0254-1© Springer-verlag London Limited 2012.

[10] Ryszard S. Chora´s, “Image Feature Extraction Techniques and Their Applications for CBIR and Biometrics Systems,” *International Journal of Biology and Bio-Medical Engineering*, Issue 1, Vol. 1, pp. 6-16, 2007.

[11] Aman Chadha, Sushmit Mallik and Ravdeep Johar, “Comparative Study and Optimization of Feature-Extraction Techniques for Content based Image Retrieval,” *International Journal of Computer Applications* (0975 – 8887) Volume 52– No.20, Aug 2012.

[12] Neetu Sharma. S1, Paresh Rawat . S2 and jaikaran Singh.S, “Efficient CBIR Using Color Histogram Processing,” *Signal & Image Processing: An International Journal (SIPIJ)* Vol.2, No.1, March 2011, DOI : 0.5121/sipij.2011.2108.

[13] Majid Fakheri, Tohid Sedghi, “Color Image Retrieval Technique Based On EM Segmentation Algorithm,” *IEEE 5th International Symposium on Telecommunications (IST'2010)*, pp.793-795, 2010.

[14] John R. Smith and Shih-Fu Chang, “Tools and Techniques for Color Image Retrieval,” Symposium on Electronic Imaging: Science and Technology-Storage and Retrieval for Image and Video Database IV, pp.426-237, 1996.

[15] Zhenhua Zhang, Wenhui Li, Bo Li, “An Improving technique of color Histogram in segmentation-based Image Retrieval,” *IEEE International conference on Information Assurance and Security*, vol. 2, pp.381 – 384, 2009.

[16] Ching-Hung Su, Huang-Sen Chiu and T Sai-Ming Hseih, “An efficient image retrieval based on HSV color space,” *IEEE International Conference Electrical and Control Engineering (ICECE),* pp. 5746 – 5749, 2011.

[17] Noureddine Abbadeni,“Computational Perceptual Features for Texture Representation and Retrieval,” *IEEE Trans. Image Process*, vol. 20, No.1, Jan 2011.

[18] V.Balamurugan,P.Anandhakumar,“Multiresolution Image Indexing Technique Based on Texture Features Using 2D Wavelet Transform,” *European Journal of Scientific Research*, ISSN 1450-216X Vol.48 No.4 (2011), pp.648-644, 2011.

[19] S. Selvarajah and S. R. Kodithuwakku, “Combined Feature Descriptor for Content Based Image Retrieval,” *IEEE 6th International Conference on Industrial and Information Systems, ICIIS* 2011, Aug. 16-19, 2011.

[20] S. Liapis and G. Tziritas, “Color and texture image retrieval using chromaticity histograms and wavelet frames,” *IEEE Trans. Multimedia,* vol. 6, no. 5, pp. 676–686, Oct. 2004.

[21] A.Grigorova, F. G. B. De Natale, C. Dagli, and T. S. Huang, “Content based image retrieval by feature adaptation and relevance feedback,” *IEEE Trans. Multimedia*, vol. 9, no. 6, pp. 1183–1192, Oct. 2007.

[22] Y. Wu and A. Zhang, “A feature re-weighing approach for relevance feedback in image retrieval,” *in Proc. IEEE Int. Conf. Image Processing (ICIP2002)*, vol. 2, pp. 581–584, 2002.

[23] Ja-Hwung Su, Wei-Jyun Huang, Philip S. Yu, Fellow, IEEE, and Vincent S. Tseng, Member, IEEE, “Efficient Relevance Feedback for Content-Based Image Retrieval by Mining User Navigation Patterns,” *IEEE Trans. Knowl. Data Eng.,* vol. 23, no. 3, Mar 2011.

[24] S. C. Hoi, M. R. Lyu, and R. Jin, “A unified log-based relevance feedback scheme for image retrieval,” *IEEE Trans. Knowl. Data Eng.,* vol. 18, no. 4, pp. 509–524, Apr. 2006.

[25] En Cheng, Feng Jing, and Lei Zhang, “A Unified Relevance Feedback Framework for Web Image Retrieval,” *IEEE Trans. Image Process*, vol. 18, no. 6, June 2009.

[26] M. R. Azimi-Sadjadi, Senior Member, IEEE, Jaime Salazar, and Saravanakumar Srinivasan, “An Adaptable Image Retrieval System With Relevance Feedback Using Kernel Machines and Selective Sampling,” *IEEE Trans. Image Process,* vol. 18, no. 7, July 2009.

[27] C. T. Hsu, Member, IEEE, and C. Y. Li, “Relevance Feedback Using Generalized Bayesian Framework With Region-Based Optimization Learning,” *IEEE Trans. Image Process*, vol. 14, no. 10, pp. 1617-1631, Oct 2005.

[28] C. Y. Li and C. T. Hsu, “Image Retrieval With Relevance Feedback Based On Graph-theoretic Region correspondence Estimation,” *IEEE Trans. Multimedia*, vol. 10, no.3, pp. 447-456, Apr 2008.

[29] Dewen Zhuang and Shoujue Wang , “Content-based image retrieval based on integrating region segmentation and relevance feedback,” *in Proc. IEEE International Conference on Multimedia Technology (ICMT),* pp. 1 - 3 , 2010.

[30] T. S. Huang, C. K. Dagli, Shyamsundar Rajaram, E. Y. Chang, M. I. Mandel, G. E. Poliner, and D. P. W. Ellis, “Active learning for interactive multimedia retrieval,” *in Proceedings of IEEE*, vol. 96, no. 4, pp. 648–667, Apr. 2008.

[31] Yo-Ping Huang, Tsun-Wei Chang and Chi-Zhan Huang, “A Fuzzy Feature Clustering with Relevance Feedback Approach to Content-Based Image Retrieval,” *in Proc IEEE International Symposium on Virtual Environments, Human-Computer Interfaces and Measurement Systems*, 2003. VECIMS '03, Pg: 57 – 62.

[32] Y. Rui, T. S. Huang, M. Ortega, and S. Mehrotra, “Relevance feedback: A power tool in interactive content-based image retrieval,” *IEEE Trans. Circuits Syst. Video Technol.*, vol. 8, no. 5, pp. 644–655, Sep. 1998.

[33] Y. Rui.and Huang, T., “Optimizing Learning in Image Retrieval,” *in Proc. IEEE Conference on Computer Vision and Pattern Recognition,* vol.1, pp.236-243, 2000.

[34] Yudong Zhang and Lenan Wu, “A Novel Method for Rigid Image Registration based on Firefly Algorithm,” *International Journal of Research and Reviews in Soft and Intelligent Computing (IJRRSIC),* Vol. 2, No. 2, June 2012.

[35] Yudong Zhang and Lenan Wu, "Rigid Image Registration by PSOSQP Algorithm," Advances in Digital Multimedia, vol. 1, pp. 4-8, 2012.

[36] J. Senthilnath, S.N. Omkar∗, V. Mani, “Clustering using firefly algorithm: Performance study,” *Swarm and Evolutionary Computation*, vol.1, pp.164–171, *Elsevier*, 2011.

[37] Mohammad Kazem Sayadia, Reza Ramezaniana* and Nader Ghaffari-Nasaba, “A Discrete Firefly Meta-heuristic with Local Search for Makespan Minimisation in permutation Flow Shop Scheduling Problems”, *International Journal of Industrial Engineering Computations*, vol. 1, pp. 1–10, 2010.

[38] T. Apostolopoulos and A. Vlachos, "Application of the Firefly Algorithm for Solving the Economic Emissions Load Dispatch Problem", *International Journal of Combinatorics*, Volume 2011, Article ID 523806, 23 pages, doi:10.1155/2011/523806.

[39] Herbert M. Gomes,” A firefly metaheuristic algorithm for structural Size and shape optimization with dynamic constraints” *Asociación Argentina de Mecánica Computacional*, pp. 2059-207 "4, 2011.

[40] Olympia Roeva, “Optimization of E. coli Cultivation Model Parameters Using Firefly Algorithm” *Int. J. Bioautomation*, vol.16, pp. 23-32, 2012.

[41] N. Chai-ead, P. Aungkulanon*, and P. Luangpaiboon, “Bees and Firefly Algorithms for Noisy Non-Linear Optimisation Problems,” *Proceedings of the International Multiconference of Engineers and Computer Scientists*, vol 2, Hong kong , 2011.

[42] Aphirak Khadwilard, Sirikarn Chansombat, Thatchai Thepphakorn, Peeraya Thapatsuwan, Warattapop Chainate and Pupong Pongcharoen, “Investigation of Firefly Algorithm Parameter Setting for Solving Job Shop Scheduling Problems,” *Operation Research Network in Thailand* , pp.89-97, 2011.

[43] Mattia Broilo, and Francesco G. B. De Natale, “A Stochastic Approach to Image Retrieval Using Relevance Feedback and Particle Swarm Optimization,” *IEEE Trans. Multimedia,* vol. 12, no. 4, June 2010.

[44] Xu Zhang, Bao-Long Guo,Guiyue Zhang,Yunyi Yan, “An Image Retrieval Method Based on r/KPSO,” *IEEE Second International Conference on Innovations in Bio-inspired Computing and Applications,* pp.69-72, 2011, DOI 10.1109/IBICA.2011.22.

[45] Chih-Chin Lai and Ying-Chuan Chen, “A User-Oriented Image Retrieval System Based on Interactive Genetic Algorithm,” *IEEE Trans on Instrumentation and Measurement,* vol. 60, no. 10, Oct 2011.

[46] Chih-Chin Lai and Ying-Chuan Chen, “An Adaptive Approach for Color Image Retrieval,” *IEEE 3rd International Conference on Communication Software and Networks (ICCSN)*, pp.137-140, 2011.

[47] X.S. Yang, Nature-Inspired Metaheuristic Algorithms, *Luniver Press*, 2008.

[48] T. Deselaers, D. Keysers, and H. Ney, “Features for image retrieval: An experimental comparison,” Inf. Retriev., vol. 11, no. 2, pp. 77–107, 2008.

ISBN: 978-988-19252-8-2
ISSN: 2078-0958 (Print); ISSN: 2078-0966 (Online)