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Query-sensitive similarity measure for content-based image retrieval using meta-heuristic algorithm

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ABSTRACT

Content based image retrieval (CBIR) systems retrieve images linked to the query image (QI) from enormous databases. The feature sets extracted by the present CBIR systems are limited. This limits the systems' effectiveness. This study extracts expansively robust and important features from the images database. These features are then kept inside the feature repository. This feature set is comprised of color signature containing features of shape and color. Here, from the given QI, features are extracted in the same manner. Accordingly, new evaluation of similarity employing a meta-heuristic algorithm (genetic algorithm with Iterated local search) is conducted between the query image features and the database images features. This study proposes CBIR system that is evaluated by investigating the number of images (from the test dataset). Meanwhile, the system's efficiency of is assessed by performing computation on the value of precision-recall for the results. The obtained results were better in comparison other advanced CBIR systems in terms of precision.

1. Introduction

Information retrieval is becoming necessary with the enormous needs of multimedia data processing to analyze the real-time data. Thus image retrieval is increasingly becoming common and recognized. It is necessary to implement and improve the tools of image retrieval in order to search or browse images on the internet easily and effectively. The conventional and common image retrieval which is based on keyword search has many drawbacks, such as the high demand of manual work and the dependency on the personal perception which results in incorrect results. To handle the above drawbacks CBIR was applied (Kanimozhi and Latha, 2013; Tseng et al., 2008, 2007; Jeon et al., 2003). This approach involves a set of methods and algorithms that concentrates on low level image features, for example texture measurements, shape and color signature to retrieve images from database of images depending on the query image (QI) given by the user (Kanimozhi and Latha, 2013).

Existing CBIR systems performance is still unsatisfactory for users of high level concepts as it principally concentrates on images' low level visual features and the high level features are not involved in the retrieval process. Therefore two approaches was improved to the first is the Region based image retrieval (RBIR) which depends on the representation of image into segmented regions features based on the image perception by user. The second is the Relevance feedback (RF) which is to ensure the inclination of user (Kanimozhi and Latha, 2013; Datta et al., 2008).

The main goal of the CBIR system is retrieving images that are relative to the QI from the images database (Carneiro et al., 2007). CBIR utilizes the technique of "query by example" which retrieves similar images to the input image by a description about the query image inputted by the user, the CBIR system works by query image features extraction, after that the system searches for the features extracted. Feature vector is calculated for the extracted features for the QI, CBIR represents every image in the database with a vector, after inputting the query image the CBIR system computes its feature vector then compares it with the vectors stored for every image in the database, the images which have high features similarity to the query image will be retrieved.

In order to enhance the image retrieval system performance the Region-based visual signatures (Kanimozhi and Latha, 2013; Yuvaraj and Hariharan, 2016) was utilized relying on the image segmentation. Based on understanding the mechanism of optical system of the human, the images must be distinguished into

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properties of region features by the image similarity. These methods compute the segmented region features at the object level and the comparisons of the similarity are executed at the region granularity where earlier conventional approaches retrieve and represent images mainly using global features.

Yang (2010) and Yang (2009) have proposed to perform image segmentation to incorporate local information into the image representation. Feng et al. (2004), a big false-image was built by gathering the entire areas of similar images; the image that was constructed is used for the RF iterations. To speed up the image retrieval process, the regions of false-image are clustered incrementally into compressed representation. Aggarwal et al. (2002), the authors modified the low-level features of input regions to create a group of images, and they derived the weights of features from these synthetic images within every query region. Then the weights of feature are accustomed by the system relying on the images that was manipulated heuristically. The authors in Chuech-Yu et al. (2004), used an adjacency matrix to represent the regions connectivity in the images, and proposed a graph based method to update the model queries based on the adjacency matrices.

Chiou-Ting and Chuech-Yu (2005), the feedback images regions are assembled to obtain the perfect query. After that, from the query, representative areas are learnt and region and feature weights are recalculated relying on the grouped results through introducing a method for optimization. The key intention for using region based methods is improving the ability to capture and interpreting the perception of user.

Several literature reviews have compared and overviewed the CBIR techniques for feature extraction in Choras (2007), Chadha et al. (1208). Also, other recent works on CBIR adopted the color descriptor. Sharma et al. (2011) have inspected two methods to describe the images content which are color histogram method global and descriptor attributes for effective retrieval. Fakheri and Sedghi (2010) made an extension for the EM-variant algorithm for Gaussians parameters estimation for detecting objects in the retrieval systems for colored image. Smith and Chang (1996) proposed a method that utilizes the back-projection of color groups for color regions extraction and color content representation, thus they provided an efficient and effective indexing and color image retrieval. Zhang et al. (2009) presented a method for color histogram representation improvement by implementing a non-uniform segmentation and quantization algorithm in an image retrieval system based on segmentation. Su et al. (2011) suggested a scheme which assigns a quantized color code for every image, then it compares the code with the database for effective image retrieval.

Also, texture is considered a vital image feature which plays a key part in the perception of human visual system (Abbadeni, 2011; Balamurugan and Anandhakumar, 2011). Both texture and color features also are major property in the systems of CBIR (Selvarajah and Kodithuwakku, 2011; Liapis and Tziritas, 2004).

So as to increase the acceptance, recent methods included the perspective of human-computer interaction (Su et al., 2011; Cheng et al., 2009; Azimi-Sadjadi et al., 2009) as well as in CBIR. Li and Hsu (2008) presented a unified graph theoretic method for significance feedback and matching image in the level of region and improved the performance of retrieval. Zhuang and Wang (2010) segmented each image into margin region and main region, and relying on the theory of High Dimensional information Geometry and then combine it with the relevance feedback, so enhanced the efficiency of retrieval. Huang et al. (2008) discussed variety of algorithms for retrieval of interactive multimedia. Huang et al. (2003), proposed a novel concept by combining the CBIR systems with the relevance feedback and the fuzzy radial basis function network (FRBFN) -based framework. Rui et al. (1998) implemented a technique for re-weighting features to incorporate relevance feedback into the CBIR systems and enhanced their effectiveness and performance. Rui and Huang (2000) implemented feature weighting based on the heuristic approach for relevance feedback incorporation into the CBIR systems and they enhanced their effectiveness and performance.

The authors in Ashraf et al. (2015) presented a method for image representation and extraction of features utilizing bandelet transform, this method returns the core information of the objects that composes an image. For image retrieval they used artificial neural networks, and for the system achievement and performance assessment, three public data sets were used, namely: Caltech 10, Corel, and Coil. In order to evaluate the retrieval efficiency, the precision and recall values were utilized.

The authors in Seetharaman and Selvaraj (2016) implemented an approach for retrieval of images by the statistical tests, for example F-ratio and Welch's t-tests. The textured and the structured query image were tested; they considered the entire image in the textured image, whereas in the structured image, they separated the image into number of regions according to its nature. The first stage of the above test is to apply F-ratio test and then the images that passes were progressed to the energy spectrum. The similar images are the image that passes both tests. For the performance verification and validation the Mean Average Precision score was utilized.

The authors in Feng et al. (2015) implemented a Global Correlation Descriptor for color and texture feature extraction, and their effect on CBIR was the same. Directional Global Correlation Vector and Global Correlation Vector also were proposed, they combined the statistics of histogram and structure element correlation benefits to define the features of color and texture respectively Corel-5K and Corel-10K datasets were utilized for validation, and for the efficiency evaluation the precision and recall were utilized.

In Zeng (2016) the authors proposed a local structure descriptor for retrieval of images. It is created based on the underlying colors of the local structures; texture, shape and color were combined for retrieval of images. In addition an algorithm was proposed to extract features by using the local structure descriptor to extract local structure histogram.

The authors in Madhavi et al. (2016) used the genetic algorithm for image retrieval by calculating number of selective features after that comparing these features for the related images. And to verify the efficiency of this approach, it was experimented on a set of 10,000 general images.

Genetic algorithm (GA) is among the common meta-heuristic algorithms, it is a search algorithm that simulates the heredity in the biological systems (Goldberg, 1989), the basic mechanism of GA is finding the best solution among the search space (Badawi and Alsmadi, 2013).

The local search algorithm is necessary to improve the performance of GA and to assist GA in exploiting the space of solutions rather than exploring the solutions space. Iterated local search (ILS) is a very effective local search algorithm, it is an excellent meta-heuristic for solving the problems of optimization. Also it is also easily and simply implemented (Badawi and Alsmadi, 2014; Avci and Topaloglu, 2017; Toksari, 2016). ILS avoids the local optima through perturbations which are applied to the on-going local minimum.

This research employed the meta-heuristic algorithm (MA) which works by applying the genetic operators on individuals followed by a local search to find the most similar images to the query image from the image database, every image is represented by one chromosome during the CBIR procedure, the shape, color texture and color signature are extracted from the QI and from the chromosomes which were generated, after that the fitness function is calculated for the chromosomes. The next step is applying the MA operations on the chromosomes such as crossover operator, mutation operator, ILS and the highest fitness chromosome selection; the most similar images to the QI will be retrieved from the database.

2. Materials and methods

2.1. Feature extraction

The CBIR system that this study proposes determines the features within the image. This is made possible via the usage of its optical contents including color signature, shape and color texture. Shown in Fig. 1 is the block diagram of the proposed method. Meanwhile, each process will be detailed in the following sections.

2.2. Color features extraction

For image retrieval, color feature is a crucial component. For image databases that are large in size, image retrieval employing the color feature is highly effective and successful. It should be noted that color feature is not a persistent parameter since it is bound to numerous non-surface characteristics. For instance, the taking conditions including illumination as well as the device's characteristics and the view point (Syam and Rao, 2013); (Alsmadi and Omar, 2012); (Alsmadi et al., 2011). The steps of the color feature extraction start with the separation of Color planes values into distinct matrices which are red, green and blue matrices. Then, computation of color histogram is made for each color matrix for each image. This is followed by the computation of variance and median of color histogram after which, the computation of the summation of all row variances and medians is performed. Next, the computed features of each matrix (R, G and B) are combined as feature vector (for each image), after generating the feature vectors for all the database images they will be stored in the database of features (Subramanian and Sathappan, 2015).

2.3. Shape features extraction

The primary aim of shape feature extraction is to capture the properties of the shape of the image items. This way, the shape storing, transmitting, comparing against, and recognizing process can become easy. It is important that the shape features are without rotation, translation, and scaling (Syam and Rao, 2013); (Alsmadi et al., 2010); (Badawi and Alsmadi, 2014). Further, the extraction of the images' shape feature requires the application of median on the gray scale image created from the RGB colored image. This is because median filter only acts on single color frequency. The Craig's formula for the conversion of RGB color image to gray scale image (Syam and Rao, 2013; Jyothi et al., 2015) is shown below.

$$I_{gs} = \begin{bmatrix} I_r & I_g & I_b \end{bmatrix} * \begin{bmatrix} 0.2989 \\ 0.587 \\ 0.114 \end{bmatrix} \tag{1}$$

where I_{gs} denotes the combined 2D matrix while $I_r.I_g.I_b$ entails the color components that generate the colored image whereas I_{gs} is symbolized as the grey level combined image. Meanwhile, salt and pepper noise and speckle noise are reduced using the median filter. Median filter has edge-preserving property and it is employed where blurring of edges is not wanted (Syam and Rao, 2013). In the context of this study, the canny edge detection method was employed to extract shape features. Edge based shape representation was employed and this provides a numerical information about image. The provided information remains the same even when there has been change in size, direction, and position of the objects in the image. When the canny edge detection operator is employed, histograms of the edge of images are constructed. Further, calculation is made for each image column mean and row mean of edge histograms. Then, all column means and row means are computed and kept in the database in the feature vector form.

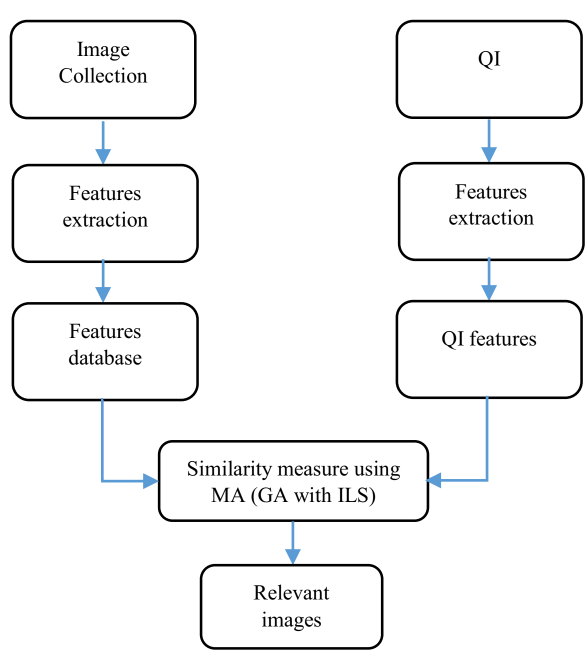

Fig. 1. Block diagram of the proposed CBIR.

2.4. Color texture features

Color texture features classification is a crucial step for image segmentation with CBIR. As such, an approach grounded on texture analysis for the classification of color texture instead of just segmentation is proposed in this study.

2.5. Grey-level co-occurrence matrix (GLCM)

The GLCM is a powerful technique of image statistical analysis (Benco et al., 2014); (Alsmadi et al., 2010); (Haralick, 1979); Nikoo et al., 2011. This technique is describable as a matrix of two dimensions of joint probabilities between pixels pairs, in which, a distance d between them in a given direction θ (Nikoo et al., 2011). Fourteen features from the GLCM for the classification of texture features were extracted and defined by Haralick and Shanmugam (1973). However, since these 14 features are greatly correlated, this study prevents this problem by employing five features to enable comparison. The steps of the color texture features extraction start with the filtering of the input image utilizing the 5×5 Gaussian Filter. Then, the filtered image is split into 4×4 blocks. Using GLCM, Standard Deviation, Correlation, Homogeneity, Entropy, Average, Contrast Dissimilarity and Energy for every block are computed. The computation of these features were according to four directions; diagonally (45^0 *and* 135^0), vertically (0^0) and horizontally (90^0). Finally, these extracted features are kept in the database of feature. Table 1 shows the GLCM features (Poulose Jacob and Vimina, 2013; Ozdemir et al., 2008).

3. Proposed meta-heuristic algorithm

The proposed meta-heuristic algorithm (genetic algorithm and Iterated local search) was originally used to create chromosomes.

Table 1
Texture features.

Name	Formula	Name	Formula
Average	$\mu i = \sum_{i,j=0}^{N-1} i(P_{i,j}) \mu j = \sum_{i,j=0}^{N-1} j(P_{i,j})$	Contrast	$\sum_{i,j=0}^{N-1} p_{i,j}(i-j)^2$
Standard Deviation	$\sigma i = \sqrt{\sigma_i^2} \sigma_j = \sqrt{\sigma_j^2}$	Dissimilarity	$\sum_{i,j=0}^{N-1} P_{i,j}\lvert i-j\rvert$
Correlation	$\sum_{i,j=0}^{N-1} \frac{(i-\mu_i)(i-\mu_j)p(i,j)}{\sigma_i \sigma_j}$	Homogeneity	$\sum_{i,j=0}^{N-1} \frac{P_{i,j}}{1+(i-j)^2}$
Entropy	$\sum_{i,j} P(i,j) log P(i,j)$	Energy	$\sqrt{\sum_{i,j=0}^{N-1} P_{i,j^2}}$

Here, the genes found within the chromosomes denote the images of the database. It is important that the chromosome has no repeated genes. Meanwhile, the values of the genes are dictated by the amount of database images that will be inquired. The features that are extracted from each image are grouped as a feature set. Extraction is also performed on the set of features from the query image. Each of the chromosomes is then subjected to the crossover, mutation (genetic operators) and Iterated local search procedures. This will produce new chromosome. As for the parameter settings of the proposed MA, they were experimentally determined. Pseudo code of the proposed MA is shown in Fig. 2.

3.1. Solution representation

The meta-heuristic algorithm (GA and ILS) that this study proposes employs a direct representation for every candidate solution (chromosomes) in the population. This consists of information on the amount of images in the database and the amount of matches in a form of binary.

3.2. The initial population

A number of chromosomes are produced randomly at first. The number of chromosomes is termed population size or *pop_size*. The amount of required images that are linked to the input query image will dictate the number of genes in every chromosome. The production of chromosome is illustrated in Fig. 3.

The GA is usually initiated via the calculation of fitness of each candidate solution in the initial population. Although the stopping criterion is not fulfilled, these processes are used: (i) The selection of a solution for reproduction by way of certain selection mechanisms (*e.g.* roulette wheel). (ii) The production of offspring by way of crossover and mutation operators. (iii) The calculation of new generations until an optimal solution is discovered or the maximum amount of generations is attained.

3.3. Crossover operation

Crossover is the key operator within the algorithm. As explained by Badawi and Alsmadi (2013), employing single cut point, crossover produces a new generation (chromosomes) from two parents. This operation determines single crossover point on both parent chromosomes selected. Here, a random number between 1 and 1c-1 is chosen and 1c denotes the chromosome length. The parent chromosomes are cut at the crossover's chosen point. Then, after that point, the components are exchanged between the parent chromosomes.

3.4. Mutation operation

The mutation operator generates random changes in solutions. This offers an opportunity for lost solutions from the population. The operation of mutation employs the method of bit-by-bit. The execution of mutation operator will take place if the ratio of

Meta-heuristic Algorithm
Set the GA parameters
Set the ILS parameters
begin
$\psi Initialize$:= generate initial solutions (population);
repeat
For offspring production two parents will be selected
Employ Reproduction operators(crossover and mutation)
Enhance offspring via ILS algorithm
population $\leftarrow$ new version (population)
***until** Termination Criterion is met*
end;
end;

Fig. 2. MA pseudo code (Moscato, 1999).

C_j	$I^j{}_1$	$I^j{}_2$	$I^j{}_3$	$I^j{}_4$	$I^j{}_5$	…….	$I^j{}_n$

Fig. 3. Chromosome form.

mutation (P_m) is verified. In the context of this study, P_m·is equivalent to 0.02 and the point that will be mutated is chosen randomly.

3.5. Iterated local search (ILS)

A local search algorithm is used prior to moving to the next generation. This will improve solution (chromosome) derived from the genetic algorithm following the performance of genetic operators. This process increases the speed of the genetic algorithm's convergence. The resulted solution from the local search is then inserted back into the genetic algorithm for the ensuing generation. The process will then ensue to the next generation and updates the population of chromosomes.

The basic idea of Iterated local search is to improve the procedure of local search through affording a new solution to start with, these solutions are obtained from the perturbed existing solutions until reaching a local optimal solution (Rossi-Doria et al., 2002). The generated solutions are better-quality than the solution from the repetitive local search trials. If the acceptance criterion is passed, it is considered as the new solution. If not passes the criterion, the previous solution is returned. The perturbations should be robust enough to allow exploring new solutions, on the other hand sufficiently weak to keep the good information added in the previous search (Rossi-Doria et al., 2002; Blum et al., 2011). A generic Iterated local search for a maximization problem is shown in Fig. 4.

As for the algorithm proposed in this study, it always accepts solutions with higher fitness values. Meanwhile, solutions with fitness values equivalent to the best solution's fitness value are accepted providing that the values contain a smaller amount of matching features. The process will ensue until the maximum amount of iterations (#Iter is set to 100) is attained.

3.6. Fitness function

With a chosen fitness function, the algorithm assesses every candidate solution from the whole population. The fitness function gives reflection on the soundness of a candidate solution. The performance of algorithm and the solution of the optimization problem are majorly dictated by the fitness function. As such, in the design phase of algorithm, the way of choosing a fitness function is highly crucial.

Determining the fitness value (quality) using the Squared Euclidean Distance for each newly produced chromosome is the next step. Fitness is dictated by the match between the image to be queried and the feature sets of the newly produced chromosomes. The chromosome with the minimum similarity difference in comparison with the input query image is considered the best chromosome. Images most relevant to the input query image are genes of the optimal obtained chromosome. The equation of the Squared Euclidean Distance is shown below (Eq. (2)).

$$\text{Squared Euclidean Distance} = Sum(f_j(I_1) - f_j(I_2))^2 \leqslant 0.009 \qquad (2)$$

In the algorithm proposed in this study, the similarity of the two images is assessed as the difference between the total of query image features and total database image features. It is important that the difference is lower than or equal to 0.009 (for instance, Squared Euclidean Distance $\leq$0.009) or the two images cannot be regarded as similar. The determination of the Squared Euclidean Distance of the fitness function proposed was experimentally done.

3.7. Selection of chromosomes

Selection entails the process that provides guidance to the algorithm towards an optimal solution by inclining towards chromosomes with high fitness. For the same purpose, this study employs a roulette wheel to select the mechanism of best retrieved images from the database according to the number of features matches. The process is done over and over until the maximum number of iterations is achieved. Then, the best chromosomes with the highest fitness number are chosen from the set of chromosomes gathered previously. These optimum chromosomes were used in the retrieval of the related images from the database of image. As such, the similar images that will be effectively retrieved comprise those containing indices represented with the genes of the best chromosomes.

4. Image dataset

The experiments in this study employed the Corel dataset which contains 10,908 different images with each image in the size of 256*384 or 384*256. As such, the outcomes were reported utilizing the ten semantic sets with every comprising of 100 images. These datasets are in the groups of Food, Buses, Elephants, Mountains, Beach, Buildings, Flowers, Africa, Horses and Dinosaurs. These groups were used in reporting the results owing to the fact that the majority of the outstanding researches, for instance, (Ashraf et al., 2015); (Madhavi et al., 2016); (Rao et al., 2011); (Youssef, 2012); Lin et al., 2009; (Jhanwar et al., 2004); (ElAlami, 2011); (Ashraf et al., 2016) employed these groups in demonstrating the effectiveness of their methods of CBIR.

5. Results and discussion

The CBIR system that this study proposed underwent test with some amount of query images. Further, retrieval was made to the similar images from the corel image database. For this purpose, extraction was made to the features including color histogram, shape and color texture from all images found in the database. Shown in Fig. 5 are the dinosaur image in different forms: original image, gray scale image, the filtered grayscale image using median filter and edge detected image using the canny algorithm. Several

```
ILS Procedure
 begin
 s0 = Generate initial solution
 Employ a local search procedure to s0 and get s
 Repeat
     Employ perturbation to s and get s'
     Employ local search procedure to s' and get s''
     If f(s'')> f(s);
     s← s''
     until Termination Criterion is met
     return s;
 end
```

Fig. 4. ILS pseudo code.

retrieved images and their query images can be viewed in Figs. 6 and 7.

Color signature was employed in this study in the calculation of features of color histogram with respect to Variance and median. The shape features were computed using the canny edge detection method while color texture was employed in the calculation of the features of GLCM with respect to standard deviation, entropy, average, correlation, dissimilarity, contrast, homogeneity as well energy. The features extracted from color signature, shape and color texture were all classified and combined in the generated feature set. Then, following the extraction of feature set from the database images, comparison was made between the feature set and that of the input query image. Here, the GA was employed in the retrieval of the similar images from the images kept in the database. Following the completion of the feature extraction process, similarity was measured using MA.

The GA produces random chromosomes (*pop_size*) with a length of *n*. Meanwhile, the amount of required images linked to the query image will dictate the amount of genes in every chromosome. The feature extraction is performed for the generated chromosomes as well as for the query image. Then, the chromosomes undergo the operation of mutation and crossover and ILS and selection mechanism for finding the optimum chromosome. After the completion of crossover, mutation and Iterated local search

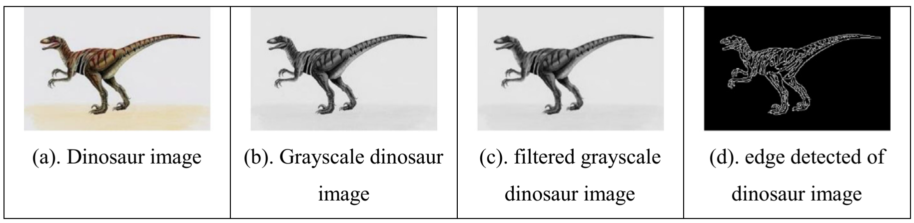

Fig. 5. Steps of shape dinosaur features extraction.

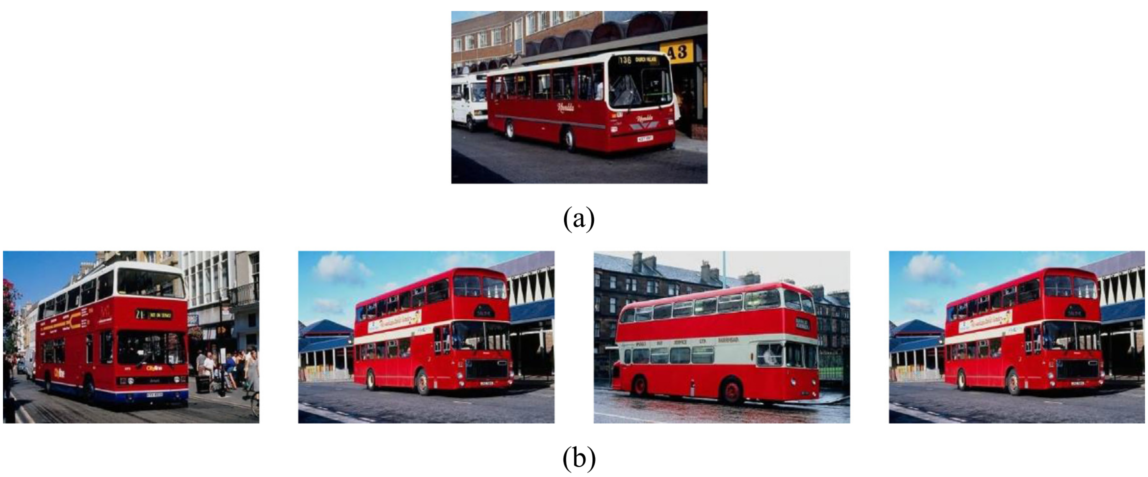

Fig. 6. a. Bus QI b. Some retrieved buses images.

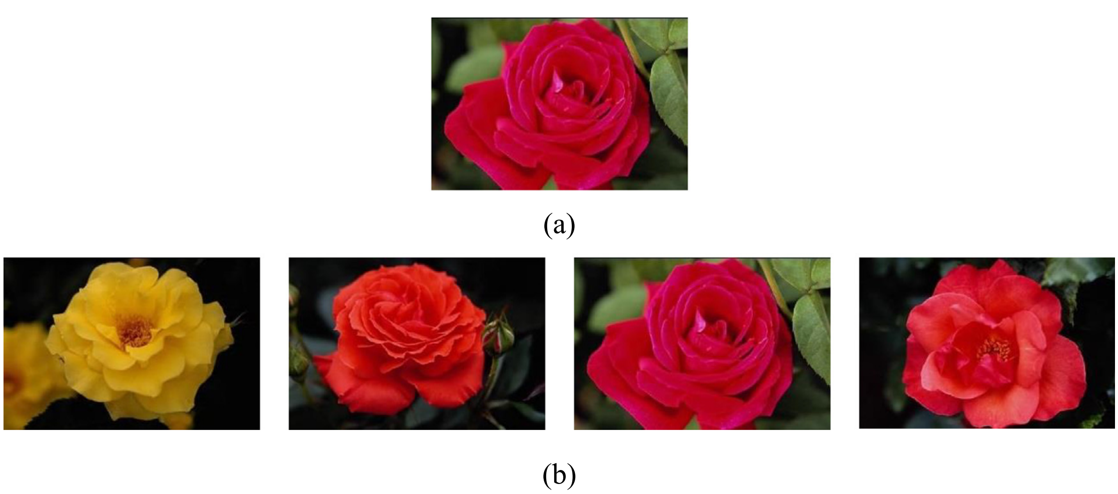

Fig. 7. a. Flower QI b. Some retrieved flowers images.

operations, selection is made to the chromosomes with the optimal values. The chosen chromosomes make up the indices of the images related to the query image. Repetition is made to this procedure until the maximum amount of iterations $Iter_{max}$ = 1000 is achieved.

5.1. Evaluation of the retrieval (Precision/Recall)

Precision (specificity) refers to a measure of the capacity of the system in retrieving just the images that are similar to the query image. Meanwhile, the Recall rate called the positive rate or sensitivity, gauges the capacity of CBIR systems in retrieving the image that are similar to the QIs. For the elaboration of the results, computation was made to precision and recall according to the number of query images (from the test dataset) and the retrieved similar images from the corel image database.

$$recall = \frac{number\ of\ similar\ image\ retrie\ ved}{tolal\ number\ of\ similar\ images\ in\ the\ databas} \tag{3}$$

$$precision = \frac{number\ of\ similar\ image\ retrie\ ved}{total\ number\ of\ images\ retrie\ ved} \tag{4}$$

Eqs. (3) and (4) comprise the calculation of the precision and recall for the query image (Syam and Rao, 2013). The recall-precision calculated for some query image and their retrieved images are presented in Table 2. Meanwhile, the graph of the exact precision-recall of the CBIR system proposed in this study is presented in Fig. 8. As evidenced by the graph, the CBIR system proposed in this study has high level of effectiveness aside from having the strength to retrieve the images. Experimentally, when more similar images are retrieved, the precision and recall will be better. The reported results by means of the extracted features combined with the techniques of MA show very promising improvements with respect to the efficiency and accuracy of the overall CBIR process.

Table 2
Recall- Precision measurements.

Groups	Precision	Recall
Buses	0.96	0.75
Mountains	0.82	0.75
Beach	0.90	0.815
Elephants	0.83	0.58
Food	0.87	0.62
Flowers	0.96	0.66
Africa	0.838	0.73
Horses	0.96	0.85
Dinosaurs	0.99	0.75
Buildings	0.755	0.62

5.2. Evaluation on Corel image set

Comparisons were made between the CBIR system proposed in this study and a number of current CBIR systems (Ashraf et al., 2015); (Madhavi et al., 2016); (Rao et al., 2011); (Youssef, 2012); Lin et al., 2009; (Jhanwar et al., 2004); (ElAlami, 2011); (Ashraf et al., 2016). This allows the measurement of the usability of the proposed method. The motivation for this selection to compare with these methods is that the results of these methods were reported via a common denomination of ten semantic sets where an individual set contains 100 images of Corel dataset. As such, it is possible to compare clear results using the reported results. This makes the performance comparison possible. The comparison of the average precision for every group of the proposed system with other comparative systems can be referred in Table 3. As evidenced by the results, the proposed system demonstrates sounder performance with respect to precision in comparison to other systems. Comparison of the average recall rates for all groups of the proposed system with the same comparative systems is shown in Table 4. The recall results of the proposed system achieved the best recall rates.

As can be deduced, the above comparison results demonstrate the capacity of the proposed system in generating better precision and recall rates. Its performance also supersedes other state-of-the-art methods (Ashraf et al., 2015); (Madhavi et al., 2016); (Rao et al., 2011); (Youssef, 2012); Lin et al., 2009; (Jhanwar et al., 2004); (ElAlami, 2011); (Ashraf et al., 2016) particularly with respect to precision and recall rates. In specific, the average precision and recall rates obtained were **0.8883** and ***0.7125*** respectively. This is factored by the fact that the authors in Ashraf et al. (2015); Madhavi et al., 2016; (Rao et al., 2011); (Youssef, 2012); Lin et al., 2009; (Jhanwar et al., 2004); (ElAlami, 2011); (Ashraf et al., 2016) created the systems of CBIR that extract a restricted number of feature sets. This restricts retrieval in terms of efficiency. On the other hand, the system proposed in this study extracted robust and extensive set of features. In this system, color signature using the technique of color histogram, shape features using the canny edge detection method and color texture using the GLCM, are employed. Also, the meta-heuristic techniques were employed for optimizing the precision of the retrieved images. The addition of the ILS

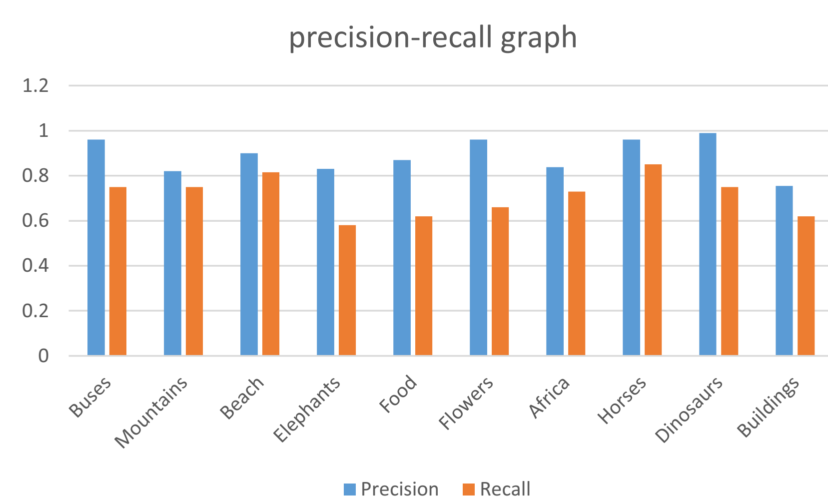

Fig. 8. Precision and Recall graph.

Table 3
The average precision results of the proposed method compared with the other standard retrieval methods.

Class	Proposed method	Madhavi et al. (2016)	Ashraf et al. (2015)	Rao et al. (2011)	Youssef (2012)	Lin et al. (2009)	Jhanwar et al. (2004)	ElAlami (2011)	Ashraf et al. (2016)
Buses	0.96	0.846	0.95	0.89	0.92	0.88	0.74	0.87	0.9
Mountains	0.82	0.811	0.75	0.51	0.74	0.52	0.29	0.53	0.7
Beach	0.90	0.892	0.70	0.53	0.64	0.54	0.39	0.56	0.75
Elephants	0.83	0.727	0.80	0.57	0.78	0.65	0.30	0.67	0.9
Food	0.87	0.871	0.75	0.69	0.81	0.73	0.36	0.74	0.8
Flowers	0.96	0.917	0.95	0.89	0.95	0.89	0.85	0.91	0.8
Africa	0.838	0.828	0.65	0.56	0.64	0.68	0.45	0.70	0.8
Horses	0.96	0.951	0.90	0.78	0.95	0.80	0.56	0.83	0.9
Dinosaurs	0.99	0.828	1.00	0.98	0.99	0.99	0.91	0.97	1
Buildings	0.755	0.632	0.75	0.61	0.70	0.54	0.37	0.57	0.75
Average	***0.8883***	***0.830***	***0.820***	***0.701***	***0.812***	***0.722***	***0.522***	***0.735***	***0.83***

Table 4
The average recall results of the proposed method compared with the other standard retrieval methods.

Class	Proposed method	Madhavi et al. (2016)	Ashraf et al. (2015)	Youssef (2012)	Lin et al. (2009)	Jhanwar et al. (2004)	ElAlami (2011)	Ashraf et al. (2016)
Buses	0.75	0.733	0.19	0.18	0.12	0.09	0.11	0.18
Mountains	0.75	0.732	0.15	0.15	0.21	0.13	0.22	0.14
Beach	0.815	0.805	0.14	0.13	0.19	0.12	0.19	0.15
Elephants	0.58	0.533	0.16	0.16	0.14	0.13	0.15	0.18
Food	0.62	0.600	0.15	0.16	0.13	0.12	0.13	0.16
Flowers	0.66	0.647	0.19	0.19	0.11	0.08	0.11	0.16
Africa	0.73	0.706	0.13	0.13	0.14	0.11	0.15	0.16
Horses	0.85	0.848	0.18	0.19	0.13	0.10	0.13	0.18
Dinosaurs	0.75	0.726	0.20	0.20	0.10	0.07	0.09	0.2
Buildings	0.62	0.585	0.15	0.14	0.17	0.12	0.18	0.15
Average	***0.7125***	***0.691***	***0.164***	***0.163***	***0.144***	***0.107***	***0.146***	***0.166***

algorithm with the GA has raised the quality of solution (weight) via the increase of the fitness number. This has helped in the improvement of the exploitation process when the searching process is being conducted. Clearly, the experimental outcomes are demonstrating the capacity of the meta-heuristic techniques in assisting the retrieval of the great amount of the relevant images to the query image.

6. Conclusion

This study recommended the effective CBIR system employing MA for the retrieval of images from databases. Once a query image is entered, the proposed CBIR performs the extraction on the image features such as color signature, shape and texture color from the image. Meanwhile, the MA based similarity measure is used to efficiently retrieve images relevant to the query image. The experiments were conducted according to the Corel image database. As shown, the proposed MA algorithm possesses strong capacity in distinguishing color, shape and color texture features. The addition of the ILS algorithm with the GA has raised the quality of solution (weight) via the increase in the fitness number. This has assisted in the improvement of the exploitation process during the process of searching. The CBIR system proposed in this study was assessed via different images query. As demonstrated by the execution results, the method is successful in retrieving the similar images from the images database. It also supersedes other proposed CBIR systems with respect to average precision and recall rates. This can be evidenced from the precision and recall values that were computed from the results of retrieval. In particular, the average precision and recall rates were **0.8883** and **0.7125** correspondingly. For the forthcoming work, the techniques of filtering will be utilized in order to attain results that are more accurate in the content based image retrieval system.

References

Abbadeni, N., 2011. Computational perceptual features for texture representation and retrieval. IEEE Trans. Image Process. 20, 236–246.

Aggarwal, G., Ashwin, T.V., Ghosal, S., 2002. An image retrieval system with automatic query modification. IEEE Trans. Multimedia 4, 201–214.

Alsmadi, M., Omar, K., 2012. Fish Classification: Fish Classification Using Memetic Algorithms with Back Propagation Classifier. LAP LAMBERT Academic Publishing.

Alsmadi, M., Omar, K.B., Noah, S.A., Almarashdeh, I., 2010. Fish recognition based on robust features extraction from size and shape measurements using neural network. J. Comput. Sci. 6, 1088–1094.

Alsmadi, M.K., Omar, K.B., Noah, S.A., Almarashdeh, I., 2010. Fish recognition based on robust features extraction from color texture measurements using back-propagation classifier. J. Theor. Appl. Information Technol. 18.

Alsmadi, M.K., Omar, K.B., Noah, S.A., 2011. Fish classification based on robust features extraction from color signature using back-propagation classifier. J. Comput. Sci. 7, 52.

Ashraf, R., Bashir, K., Irtaza, A., Mahmood, M.T., 2015. Content based image retrieval using embedded neural networks with bandletized regions. Entropy 17, 3552–3580.

Ashraf, R., Bashir, K., Mahmood, T., 2016. Content-based image retrieval by exploring bandletized regions through support vector machines. J. Inform. Sci. Eng. 32, 245–269.

Avci, M., Topaloglu, S., 2017. A multi-start iterated local search algorithm for the generalized quadratic multiple knapsack problem. Comput. Oper. Res. 83, 54–65.

Azimi-Sadjadi, M.R., Salazar, J., Srinivasan, S., 2009. An adaptable image retrieval system with relevance feedback using kernel machines and selective sampling. IEEE Trans. Image Process. 18, 1645–1659.

Badawi, U.A., Alsmadi, M.K.S., 2013. A hybrid memetic algorithm (Genetic Algorithm and Great Deluge Local Search) with back-propagation classifier for fish recognition. Int. J. Comput. Sci. Issues 10, 348–356.

Badawi, U.A., Alsmadi, M.K., 2014. A general fish classification methodology using meta-heuristic algorithm with back propagation classifier. J. Theoret. Appl. Information Technol. 66.

Balamurugan, V., Anandhakumar, P., 2011. Multiresolution image indexing technique based on texture features using 2D wavelet transform. Eur. J. Sci. Res. 48, 648–664.

Benco, M., Hudec, R., Kamencay, P., Zachariasova, M., Matuska, S., 2014. An Advanced Approach to Extraction of Colour Texture Features Based on GLCM. Int. J. Adv. Rob. Syst. 11.

Blum, C., Puchinger, J., Raidl, G.R., Roli, A., 2011. Hybrid metaheuristics in combinatorial optimization: A survey. Applied Soft Computing 11, 4135–4151.

Carneiro, G., Chan, A.B., Moreno, P.J., Vasconcelos, N., 2007. Supervised learning of semantic classes for image annotation and retrieval, Pattern Analysis and Machine Intelligence, IEEE Transactions on, vol. 29, pp. 394–410.
Chadha, A., Mallik, S. Johar, R. Comparative study and optimization of feature-extraction techniques for content based image retrieval, arXiv preprint arXiv:1208.6335, 2012.
Cheng, E., Jing, F., Zhang, L., 2009. A unified relevance feedback framework for web image retrieval. IEEE Trans. Image Process. 18, 1350–1357.
Chiou-Ting, H., Chuech-Yu, L., 2005. Relevance feedback using generalized Bayesian framework with region-based optimization learning. IEEE Trans. Image Process. 14, 1617–1631.
Choras, R.S., 2007. Image feature extraction techniques and their applications for CBIR and biometrics systems. Int. J. Biol. Biomed. Eng. 1, 6–16.
Chuech-Yu, L., Ming-Chou, S., Chiou-Ting, H. Image retrieval with relevance feedback based on graph-theoretic region correspondence estimation. In: Proceedings of the 17th International Conference on Pattern Recognition, 2004. ICPR 2004, vol. 3, 2004, pp. 842–845.
Datta, R., Joshi, D., Li, J., Wang, J.Z., 2008. Image retrieval: ideas, influences, and trends of the new age. ACM Comput. Surveys (Csur) 40, 5.
ElAlami, M.E., 2011. A novel image retrieval model based on the most relevant features. Knowl.-Based Syst. 24, 23–32.
Fakheri, M. Sedghi, T. 2010. Color image retrieval technique based on em segmentation algorithm. In: Telecommunications (IST), 2010 5th International Symposium on, 2010, pp. 793–795.
Feng, J., Mingjing, L., Hong-Jiang, Z., Bo, Z., 2004. Relevance feedback in region-based image retrieval. IEEE Trans. Circuits Syst. Video Technol. 14, 672–681.
Feng, L., Wu, J., Liu, S., Zhang, H., 2015. Global correlation descriptor: a novel image representation for image retrieval. J. Vis. Commun. Image Represent. 33, 104–114.
Goldberg, D.E., 1989. Genetic Algorithms in Search, Optimization and Machine Learning. Addison-Wesley Longman Publishing Co., Inc.
Haralick, R.M., 1979. Statistical and structural approaches to texture. Proc. IEEE 67, 786–804.
Haralick, R.M. Shanmugam, K., 1973. Textural features for image classification. In: IEEE Transactions on systems, man, and cybernetics, pp. 610–621.
Huang, Y.-P., Chang, T.-W., Huang, C.-Z., 2003.A fuzzy feature clustering with relevance feedback approach to content-based image retrieval. In: Virtual Environments, Human-Computer Interfaces and Measurement Systems, 2003. VECIMS'03. 2003 IEEE International Symposium on, 2003, pp. 57–62.
Huang, T.S., Dagli, C.K., Rajaram, S., Chang, E.Y., Mandel, M.I., Poliner, G.E., Ellis, D.P., 2008. Active learning for interactive multimedia retrieval. Proc. IEEE 96, 648–667.
Jeon, J., Lavrenko, V., Manmatha, R., 2003. Automatic image annotation and retrieval using cross-media relevance models. In: Proceedings of the 26th annual international ACM SIGIR conference on Research and development in information retrieval, pp. 119–126.
Jhanwar, N., Chaudhuri, S., Seetharaman, G., Zavidovique, B., 2004. Content based image retrieval using motif cooccurrence matrix. Image Vis. Comput. 22, 1211–1220.
Jyothi, G., Sushma, C., Veeresh, D.S.S., 2015. Luminance based conversion of gray scale image to RGB image. Int. J. Comput. Sci. Information Technol. Res. 3, 279–283.
Kanimozhi, T., Latha, K., 2013. A Meta-heuristic optimization approach for content based image retrieval using relevance feedback method. In: Proceedings of the World Congress on Engineering 2013 London, U.K.
Li, C.-Y., Hsu, C.-T., 2008. Image retrieval with relevance feedback based on graph-theoretic region correspondence estimation. IEEE Trans. Multimedia 10, 447–456.
Liapis, S., Tziritas, G., 2004. Color and texture image retrieval using chromaticity histograms and wavelet frames. IEEE Trans. Multimedia 6, 676–686.
Lin, C.-H., Chen, R.-T., Chan, Y.-K., 2009. A smart content-based image retrieval system based on color and texture feature. Image Vis. Comput. 27, 658–665.
Madhavi, K.V., Tamilkodi, R., Sudha, K.J., 2016. An innovative method for retrieving relevant images by getting the top-ranked images first using interactive genetic algorithm. Proc. Comput. Sci. 79, 254–261.
Moscato, P., 1999. Memetic algorithms: a short introduction. In: David, C., Marco, D., Fred, G., Dipankar, D., Pablo, M., Riccardo, P., Kenneth, V.P. (Eds.), New ideas in Optimization. McGraw-Hill Ltd., UK, pp. 219–234.
Nikoo, H., Talebi, H., Mirzaei, A., 2011. A supervised method for determining displacement of gray level co-occurrence matrix. In: Machine Vision and Image Processing (MVIP), 2011 7th Iranian, pp. 1–5.
Ozdemir, I., Norton, D.A., Ozkan, U.Y., Mert, A., Senturk, O., 2008. Estimation of tree size diversity using object oriented texture analysis and aster imagery. Sensors 8, 4709–4724.
Poulose Jacob, K., Vimina, E., 2013. Content based image retrieval using low level features of automatically extracted regions of interest.
Rao, M.B., Rao, B.P., Govardhan, A., 2011. CTDCIRS: content based image retrieval system based on dominant color and texture features. Int. J. Comput. Appl. 18, 40–46.
Rossi-Doria, O., Sampels, M., Birattari, M., Chiarandini, M., Dorigo, M., Gambardella, L.M., Knowles, J., Manfrin, M., Mastrolilli, M., Paechter, B., Paquete, L., Stützle, T., 2002. A comparison of the performance of different metaheuristics on the timetabling problem. In: Burke, E., De Causmaecker, P. (Eds.), Practice and Theory of Automated Timetabling IV: 4th International Conference, PATAT 2002, Gent, Belgium, August 21–23, 2002. Selected Revised Papers. Springer, Berlin Heidelberg, Berlin, Heidelberg, pp. 329–351.
Rui, Y., Huang, T., 2000. Optimizing learning in image retrieval. In: Computer Vision and Pattern Recognition, 2000. Proceedings. IEEE Conference on, pp. 236–243.
Rui, Y., Huang, T.S., Ortega, M., Mehrotra, S., 1998. Relevance feedback: a power tool for interactive content-based image retrieval. IEEE Trans. Circuits Syst. Video Technol. 8, 644–655.
Seetharaman, K., Selvaraj, S., 2016. Statistical tests of hypothesis based color image retrieval. J. Data Anal. Information Process. 4, 90.
Selvarajah, S., Kodithuwakku, S., 2011. Combined feature descriptor for content based image retrieval. In: Industrial and Information Systems (ICIIS), 2011 6th IEEE International Conference on, 2011, pp. 164–168.
Sharma, N.S., Rawat, P.S., Singh, J.S., 2011. Efficient CBIR using color histogram processing. Signal Image Process. 2.
Smith, J.R., Chang, S.-F., 1996. Tools and techniques for color image retrieval. Electron. Imag. Sci. Technol., 426–437
Su, C.-H., Chiu, H.-S., Hsieh, T.-M. 2011. An efficient image retrieval based on HSV color space. In Electrical and Control Engineering (ICECE), 2011 International Conference on, 2011, pp. 5746–5749.
Su, J.-H., Huang, W.-J., Philip, S.Y., Tseng, V.S., 2011. Efficient relevance feedback for content-based image retrieval by mining user navigation patterns. IEEE Trans. Knowl. Data Eng. 23, 360–372.
Subramanian, M., Sathappan, S., 2015. An efficient content based image retrieval using advanced filter approaches. Int. Arab J. Information Technol. (IAJIT) 12.
Syam, B., Rao, Y., 2013. An effective similarity measure via genetic algorithm for content based image retrieval with extensive features. Int. Arab J. Inform. Technol. (IAJIT) 10.
Toksari, M.D., 2016. A hybrid algorithm of ant colony optimization (ACO) and iterated local search (ILS) for estimating electricity domestic consumption: case of Turkey. Int. J. Electr. Power Energy Syst. 78, 776–782.
Tseng, V.S., Su, J.-H., Wang, B.-W., Lin, Y.-M., 2007. Web image annotation by fusing visual features and textual information. In: Proceedings of the 2007 ACM symposium on Applied computing, pp. 1056–1060.
Tseng, V.S., Su, J.-H., Huang, J.-H., Chen, C.-J., 2008. Integrated mining of visual features, speech features, and frequent patterns for semantic video annotation. IEEE Trans. Multimedia 10, 260–267.
Yang, X.-S. 2009. Firefly algorithms for multimodal optimization. In: O. Watanabe, T. Zeugmann (eds.), Stochastic Algorithms: Foundations and Applications: 5th International Symposium, SAGA 2009, Sapporo, Japan, October 26–28, 2009. Proceedings, Berlin, Heidelberg, Springer, Berlin Heidelberg, pp. 169–178.
Yang, X.-S., 2010. Firefly algorithm, stochastic test functions and design optimisation. Int. J. Bio-Inspired Comput. 2, 78–84.
Youssef, S.M., 2012. ICTEDCT-CBIR: integrating curvelet transform with enhanced dominant colors extraction and texture analysis for efficient content-based image retrieval. Comput. Electr. Eng. 38, 1358–1376.
Yuvaraj, D., Hariharan, S., 2016. Content-based image retrieval based on integrating region segmentation and colour histogram. Learning 2, 12.
Zeng, Z., 2016. A novel local structure descriptor for color image retrieval. Information 7, 9.
Zhang, Z., Li, W., Li, B., 2009.An improving technique of color histogram in segmentation-based image retrieval. In: Information Assurance and Security, 2009. IAS'09. Fifth International Conference on, 2009, pp. 381–384.
Zhuang, D., Wang, S., 2010. Content-based image retrieval based on integrating region segmentation and relevance feedback. In: Multimedia Technology (ICMT), 2010 International Conference on, 2010, pp. 1–3.