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An artificial bee colony algorithm for image contrast enhancement

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ABSTRACT

Image Enhancement is a crucial phase in almost every image processing system. It aims at improving both the visual and the informational quality of distorted images. Histogram Equalization (HE) techniques are the most popular approaches for image enhancement for they succeed in enhancing the image and preserving its main characteristics. However, using exhaustive approaches for histogram equalisation is an algorithmically complex task. These HE techniques also fail in offering good enhancement if not so good parameters are chosen. So, new intelligent approaches, using Artificial Intelligence techniques, have been proposed for image enhancement. In this context, this paper proposes a new Artificial Bee Colony (ABC) algorithm for image contrast enhancement. A grey-level mapping technique and a new image quality measure are used. The algorithm has been tested on some test images, and the comparisons of the obtained results with the genetic algorithm have proven its superiority. Moreover, the proposed algorithm has been extended to colour image enhancement and given very promising results. Further qualitative and statistical comparisons of the proposed ABC to the Cuckoo Search (CS) algorithm are also presented in the paper; not only for the adopted grey-level mapping technique, but also with using another common transformation, generally called the local/global transformation.

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1. Introduction

Image processing is a very active area of research in computing. It has many applications in everyday life tasks, from medicine to transportation and industry. This operation includes all operations applied on digital images that aim at changing the photometric or structural characteristics of the image. Image enhancement is a crucial stage in almost every image processing system. The objective of image enhancement is to improve the interpretability of the information present in the image for human viewers. An enhancement algorithm is one that yields a better-quality image for the purpose of some particular application. It is generally accomplished through suppressing noise or by increasing contrast [1,2].

Although, its crucial role in aiding other phases of image processing systems, very few high-level approaches have been proposed for image enhancement; generally, filtering techniques are adopted. Among the difficulties that prevented image enhancement from evolving as intensively as other image processing tasks (registration, segmentation, etc.), is the difficulty of quantifying image quality; since image quality is a very subjective concept: succeeding in judging images as good or not is almost restricted to humans.

Recently, some image quality measures have been proposed and used for grey-level image enhancement. One powerful category of measures is that combining the number of edge pixels, the intensities of these pixels and the entropy of the whole image. This category of measures has been successfully exploited in the context of image enhancement using Differential Evolution (DE) [3], Particle Swarm Optimisation (PSO) [4] and the Cuckoo Search (CS) algorithm [5] as optimisation approaches.

A Genetic Algorithm (GA) for image enhancement was proposed in [6] for image enhancement through contrast enhancement. It uses the genetic algorithm to look for the optimal mapping of the grey levels of the input image into new grey levels offering better contrast for the image. The good results reported by the authors motivated us to apply a newer and better performing metaheuristic: the Artificial Bee Colony (ABC) [7]. This relatively new metaheuristic has proved to be very efficient in solving optimisation algorithms. It has even proved to be superior than both conventional genetic algorithm and the PSO [8]. Thus, many various of the ABC have been proposed and implemented for solving variant optimisation problems, but no variant, even the basic one, has been applied in the context of image enhancement.

In this perspective, the present paper presents a new artificial bee colony algorithm for image contrast enhancement based on searching the best alternative set of grey levels. As an objective function, a new formula is used. It is calculated using the number

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of edge pixels, the intensities of these pixels and the image entropy. The proposed algorithm has been evaluated by applying it on a set of test images and offered very promising results. First, the algorithm has been devised for grey-level images. Then, it has been extended to enhance colour images.

As further means of validation of findings, detailed qualitative and statistical comparisons with the recently proposed Cuckoo Search (CS) algorithm are presented. Moreover, the proposed ABC has been adapted to the so-called local/global transformation for image enhancement [3–5,9,10], and again compared to the CS algorithm, for the same transformation adopted in this work. The obtained results in both cases of transformation have proved the superiority of the proposed ABC algorithm.

Consequently, the rest of this paper will be organised as follows. In Section 2, basic concepts of image enhancement and a brief introduction to the ABC algorithm are presented. The proposed ABC algorithm for image enhancement is presented in Section 3. The obtained results of applying the proposed approach on a set of test images are presented and discussed in Section 4. Comparisons with state-of-the-art approaches are detailed in the same section. Finally, some conclusions and future research directions are drawn up in Section 5.

2. Basic concepts

2.1. Image enhancement

Image enhancement can be defined as being the operation that aims at changing the photometric characteristics of an image, such as contrast, so that it looks better, becomes easier to interpret and to be used in further steps of any automatic image processing system. We can also say that image enhancement aims at improving the interpretability or perception of information in images for human viewers and providing 'better' input for other automated image processing techniques. So, the main objective of image enhancement is to modify the image attributes to make it more suitable for a given task or a specific observer [2]. For instance, image enhancement is essential in any medical image diagnosis system. Another important application of image enhancement is the enhancement of iris, fingerprint or even palmprint images in biometric recognition systems.

There exist two basic categories of approaches to images enhancement: *filtering techniques* and *contrast enhancement methods*. Filtering consists of the substitution of every pixel of the input image by a value calculated from the original value of that pixel and the values of its neighbouring pixels; whereas contrast enhancement is the operation that maps the grey levels of the input image to a new set of grey levels in order to get a more homogeneous distribution of these levels [6,11]. In other words, contrast enhancement allows grey levels of the histogram to become flatter (Fig. 1), this is generally what characterises homogeneous, easily interpretable and easily analysed images.

One of the simplest and most popular ways to accomplish contrast enhancement is *global intensity transformation*. In this method, by utilising lookup tables, the intensity levels in an image are mapped into a new set of grey levels, which leads to changing the image parameters such as contrast. This technique is called 'global' since it performs intensity transformation on all grey levels of the image, and not only on a group of them. The main objective in global intensity transformation is to obtain a lookup table or transfer function which yields an output image with improvement or desired parameters. In the case of contrast enhancement, the desired transfer function should map intensity levels in a way that permits the increase of the contrast of the image, while preserving its natural look [12]. Unlike global techniques, local techniques either apply different functions on different areas of the image or pixels of the input image; or they use different parameters in the same function to apply changes.

In this paper, a global technique for contrast enhancement is used. It maps grey levels of the input image into a new set of grey levels. Here, as will be seen in next sections, an ABC algorithm is the optimiser that is used to find the new set of grey levels.

2.2. Artificial bee colonies

The Artificial Bee Colony (ABC) algorithm is a swarm-based metaheuristic that was first introduced by Karaboga and Basturk in 2005 [7] for solving numerical optimisation problems. This metaheuristic was inspired by the intelligent foraging behaviour of natural honeybees. In a natural bee swarm, the food search is collectively performed by three kinds of honeybees: *the employed bees*, *the onlookers* and *the scouts*.

The employed bees search food around the food sources in their memories and share information about the newly found food sources with the onlookers via the waggle dance. The onlookers select good food sources among those found by the employed bees, and search around them for better food sources. The scouts tend to search for new food sources randomly [13].

Inspired by this natural behaviour, the artificial version of bee swarm behaves as follows. The population in an artificial bee colony is subdivided into three sub-groups: employed bees, onlookers and scouts. The number of the employed bees is equal to the number of the onlookers and to that of the number of solutions [14]. These artificial bees fly around in a multidimensional search space and choose food sources which are possible solutions to the problem to bee solved. The employed and onlooker bees search depends on their self-experience and on that of their mates, while the scouts search is random. The associated nectar amount to each food source corresponds to the fitness fit_i of the associated solution. For minimization problems, the nectar amount is calculated using Eq. (1), where f_i is the fitness value of the current solution [14]:

$$fit_i = \begin{cases} 1/(1+f_i) & \text{if } f_i \geq 0, \\ 1+abs(f_i) & \text{if } f_i < 0. \end{cases} \tag{1}$$

The ABC algorithm follows an iterative process whereby the concerned bees move towards better solutions by means of a neighbour search mechanism in which poor solutions are abandoned. As shown in the pseudo-code of Fig. 2; after an initialization phase, the ABC algorithm repeats cyclically, till meeting a stop condition, three basic stages: the employed bee stage, the onlooker stage and the scout stage [13,14].

2.2.1. Initialization

Initially, all food sources are considered as solution vectors x_i to the optimisation problem in question. Each vector x_i is composed of n variables, $x_{ij}, j = 1, \ldots n$, to be optimised in order to minimise (or maximise) the objective function. These solution vectors are initially generated using Eq. (2), where l_j and u_j are the lower and upper bounds of the parameter x_{ij} respectively:

$$x_{ij} = l_j + rand(0,1) * (u_j - l_j) \tag{2}$$

2.2.2. Employed bee stage

During each iteration of the algorithm, each employed bee determines a new food source v_i in the neighbourhood of its currently associated food source x_i, and evaluates its nectar's amount. Eq. (3) is used for this purpose, where x_k is a randomly selected food source, j is a randomly chosen parameter index and

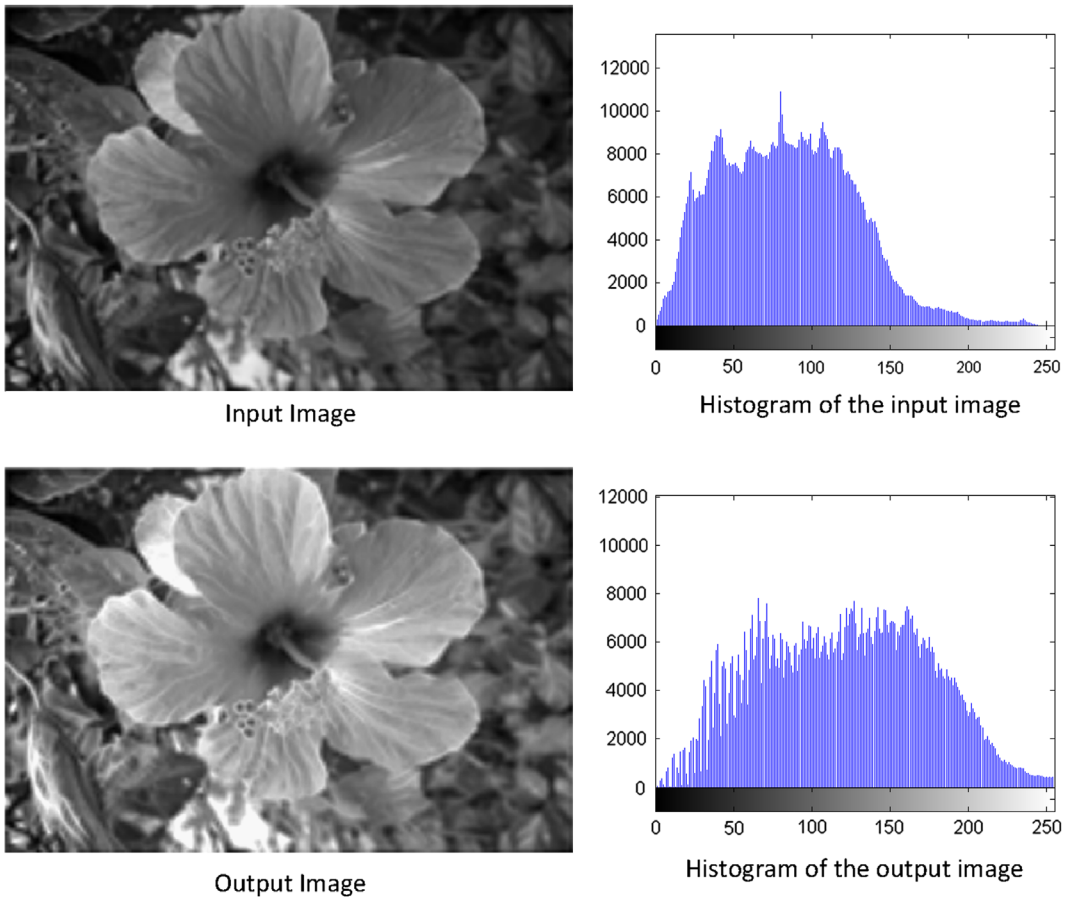

Fig. 1. Image enhancement.

Initialization;

Repeat

Employed bee stage: Perform an update process for each solution in the solution population;

Onlooker stage: Randomly select solutions depending on their fitness values, then perform the same update process for each selected solution;

Scout stage: Select one of the most inactive solutions, and then replace it by a new randomly generated solution;

Until (stop condition is met)

Fig. 2. General framework of the ABC algorithm.

ϕ_{ij} is a random number within the range $[-1, 1]$:

$$v_{ij} = x_{ij} + \phi(x_{ij} - x_{kj}) \tag{3}$$

If the nectar amount of the newly generated solution v_i is better than that of its currently associated food source x_i, then the employed bee moves to this new food source abandoning the old one, using a greedy selection approach; otherwise, it remains at its old food source.

2.2.3. Onlooker stage

After all employed bees have completed their work, as described above; they share the nectar information of food sources with the onlookers. Consequently, each onlooker bee selects probabilistically a food source according to its nectar amount using the *roulette wheel selection* method. The probability P_i with which a food source is selected by an onlooker is given by Formula (4), where fit_i is the fitness of solution i and n is the total number of food sources:

$$P_i = fit_i / \Sigma_n fit_n \tag{4}$$

After choosing a food source by the onlooker bee, it will be perturbed using the same process described in Eq. (3). Then, again, a greedy selection is applied between the probabilistically chosen food source and the one obtained from the perturbation process.

2.2.4. Scout stage

The scout stage takes place when a food source is abandoned. Algorithmically speaking, this means that the fitness value of the considered solution has not improved for a given number of generations. This number of generations *limit* is generally taken to be $limit = D * popSize$, where D is the problem dimension (the number of variables to be optimised) and *popSize* is the number of the employed bees or the onlookers (the number of solutions) [13,14]. If this condition is met, scouts regenerate new food sources using the same equation of the initialisation step, Eq. (2).

Since its invention, the ABC algorithm has received an increasing interest because of its simplicity and wide applicability. The basic version of the ABC and many other variants of the algorithm have been successfully applied to solve academic and real world problems. For instance, Zhu and Kwong [13] proposed a *Gbest-guided ABC* algorithm for solving numerical optimisation problems. An ABC algorithm was devised by Sundar and Singh [15] to solve the 0–1 multidimensional knapsack problem. In [16], Srinivasa Rao et al. used the ABC for the optimization of distribution network configuration for loss reduction. The ABC was also used for neural network training [17], for digital IIR filters [18], and for solving the leaf constrained minimum spanning tree problem

[19]. Besides, a discrete version of the ABC algorithm was proposed. It was well adapted to solve combinatorial optimisation problems such as the travelling salesman problem [20].

As far as image processing is concerned, we find that the ABC algorithm has been widely exploited. For example, Miao et al. [21] have proposed an ABC algorithm for SAR (Synthetic Aperture Radar) Image segmentation. Another very active application of the ABC in the field of image processing is that of multi-level thresholding. It has been treated by many works and through different techniques [22–24]. Xu and Duan [25] have presented an ABC algorithm for low-altitude aircraft target recognition. In addition, the ABC algorithm has been successfully used for optimising artificial neural networks in the context of image deblurring [26].

3. The proposed ABC algorithm for contrast enhancement

As mentioned above, the present work uses an ABC approach for image contrast enhancement. The set of grey levels of the input image is substituted by a new set that gives more homogeneity to the image histogram, and so offers better quality of the image. The new set of grey levels is got by using the ABC algorithm as an optimiser. In fact, the exhaustive search of the better mapping would be very time-consuming, which motivates the use of metaheuristics.

Considering contrast enhancement as an optimisation problem gives rise to the necessity of defining two aspects: *the representation of solutions* and *the objective function*. In this section, we start by defining these two elements, then the use of the ABC for accomplishing the task of finding optimal grey-level mapping is presented.

3.1. Representation of solutions

A vectorial representation of solutions has been used in [6]. The same representation is adopted in the present work. Accordingly, a solution to the problem is an ordered vector of D integers in the interval $[0, 255]$ representing a possible mapping of the grey levels of the input image, where D is the number of grey levels in the input image. Fig. 3 illustrates this representation in which A is the ascendantly ordered vector of the grey levels in the input image, B is a solution to the problem and C and D are the corresponding histograms.

Thus, the output image will be that obtained from applying the correspondence of each grey level in the input image to the equivalent grey level in the solution vector (the grey level having the same position). Taking as an example the mapping shown in Fig. 3, we find that the mapping function, that will be applied to pixels' intensities of the input image, has the following description: $f(15)=0$, $f(57)=40$, $f(73)=64$, $f(80)=119$ and $f(240)=255$.

Hence, the population of solutions is a set of ascendantly sorted integer vectors of dimension D having values in the interval $[0, 255]$. Of course the descendant ordering of solutions can also be used, in this case the mapping will correspond to the descendent order of the input vector.

3.2. Objective function

To evaluate the quality of solutions in our ABC algorithm, we adopted a formula that combines the number of edge pixels, the intensity of edge pixels and the entropy of the whole image. This formula is given in Eq. (5), basically used in [3,4,10,27]. This formula principally differs from that used in [6], Eq. (6), in the use of the entropy as an additional component in its calculation; since the greater the entropy of the image is, the better its quality is:

$$F(Z) = \log(\log(E(I(Z)))) \cdot \frac{ne(I(Z))}{PH \times PV} \cdot H(I(Z)) \tag{5}$$

$$F(Z) = \log(\log(E(I(Z)))) \cdot ne(I(Z)) \tag{6}$$

In the formulas,

- $F(Z)$ represents the quality of the output image obtained from the use of the mapping represented by the solution vector Z on the input image I.
- $E(I(Z))$ is the sum of edge intensities of the image resulting from filtering the output image $I(Z)$ by the *Sobel filter*.
- $ne(I(Z))$ is the number of the edges in the same resulting image.
- $H((I(Z)))$ is the entropy of the output image.
- PH and PV are the numbers of horizontal and vertical pixels of the image respectively.

3.3. The search process

In our approach, an artificial bee colony is used as an optimiser to search for the best mapping that maximises the objective function. As summarised in the chart of Fig. 4, once the image to be enhanced is introduced to the system, the following steps are applied.

1. *Initialisation*: An initial population of solutions Pop_0 is generated. It consists of n ascendantly ordered integer vectors having values in the interval [0, 255]. n represents the number of solutions; it is the number of the employed bees and the onlookers. The number of elements of these vectors is D which represents the number of grey levels of the input image.

After this initialisation, the algorithm repeats the following steps cyclically till a stop condition is met. In this work, the stop condition has been chosen to be a predefined number of iterations.

2. *The employed bee stage*: In this stage, each employed bee acts as follows:

- The bee creates a new solution from a randomly chosen one, using the principle described in Eq. (3).

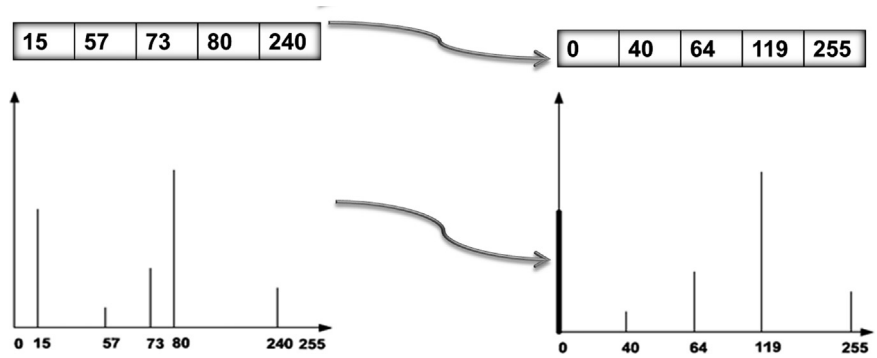

Fig. 3. Grey-levels mapping and solution representation.

- A correction operation takes place, it consists of discretising, sorting and bounding the obtained solutions; since the search equation works in the continuous space while we treat in this work a discrete problem (mapping grey-levels), we need to discretise solutions. Bounding operation permits delimiting solutions between 0 and 255.
- According to the value of their fitnesses, the bee chooses the best solution between that randomly chosen and the newly created one. To evaluate a given solution means to calculate the value of the objective function, described in Eq. (5), on an output image obtained from grey-level mapping, of input grey levels, using the solution in question.

3. *The onlookers stage*: In this phase, the onlookers look for better solutions in a similar manner to the employed bees, but with a slight difference. In this stage, for each bee, the choice of the solution to be perturbed, whose neighbourhood will be explored, is based on the quality of solutions; good solutions will be favoured, and the weak ones are relatively discarded. Hence, this phase consists of the following operations:

- Each onlooker chooses a corresponding solution according to the *roulette policy*.
- The onlooker creates a new solution in the neighbourhood of the corresponding chosen solution with the same process described in Eq. (3).
- Correcting the obtained solutions in the same way as explained in the employed bee stage.
- The best solution between the old and the newly created one, having the best objective-function value, is kept.

4. *The scouts stage*: In this step, one of the most inactive solutions is replaced by a new one generated randomly, according to the same process of the initialisation step, i.e. generating an

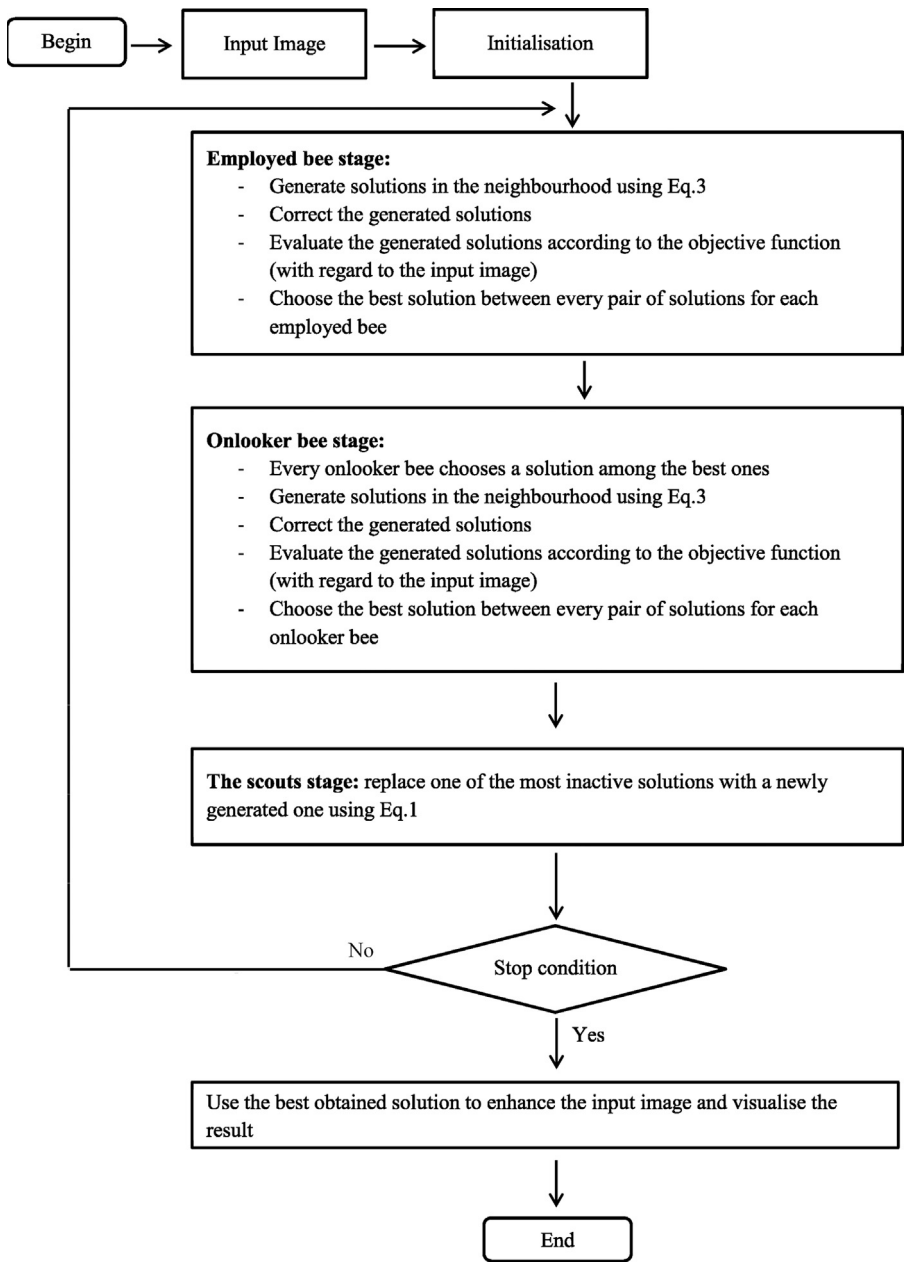

Fig. 4. The proposed ABC Approach for contrast enhancement.

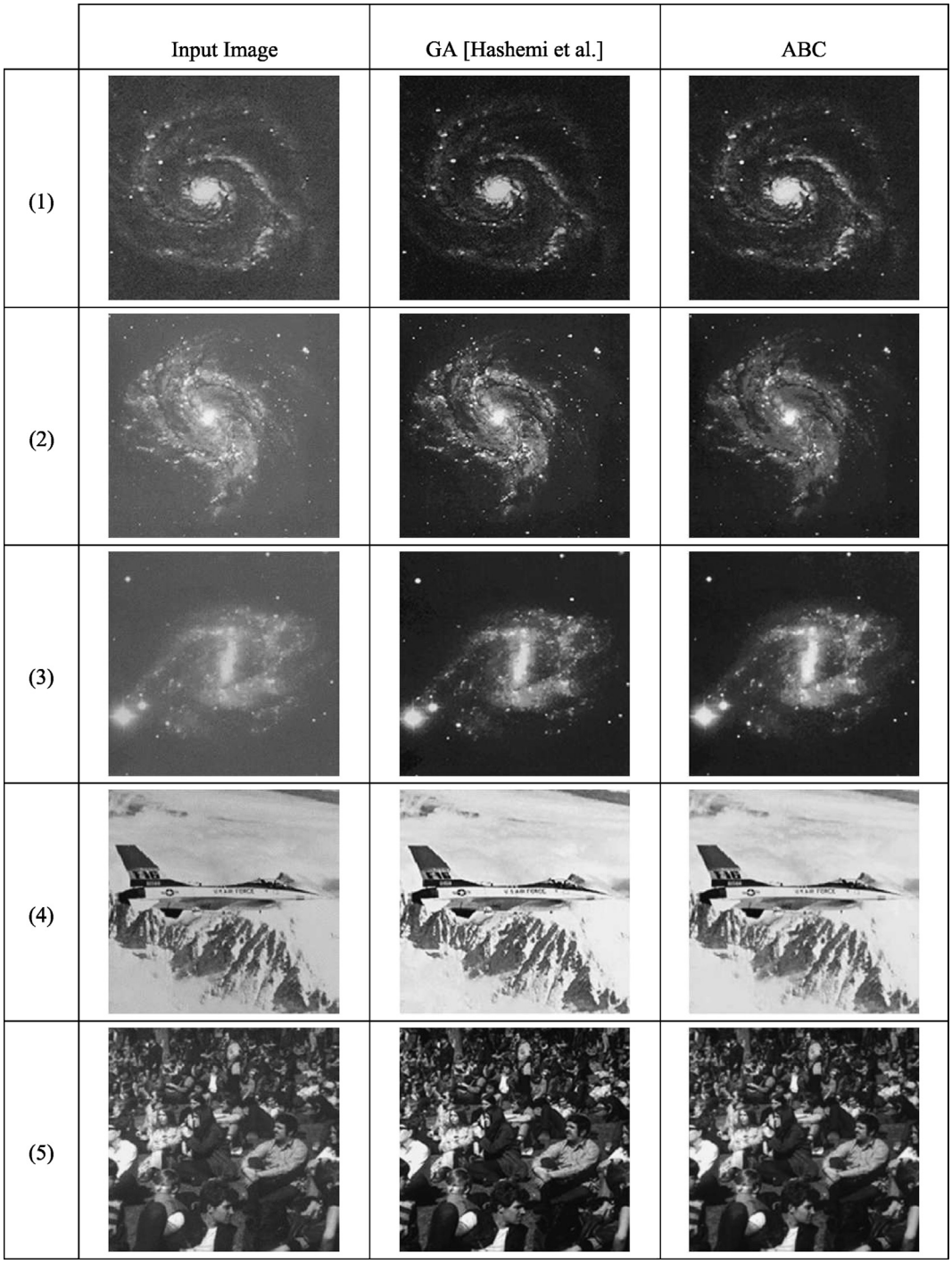

Fig. 5. Enhancement of the benchmark images, compared with [6].

ascendantly sorted vector of integers between 0 and 255. An inactive solution is defined to be a solution that has not been replaced for at least *limit* generations.

5. *Check the stop condition*: If the stop condition is met, the best solution found so far is applied to transform the input image into the result image, which represents the enhanced image, the result is then visualised.

4. Experimental results

In this section, the proposed algorithm is validated through applying it on a set of test images. The validation process is composed of two main parts. First, the proposed algorithm is compared to the work of Hashemi et al. proposed in [6], we also give some qualitative results in the same sub-section. Second, our algorithm is compared to the Cuckoo Search algorithm. The latter comparison itself consists of two sub-comparisons; with regard to the adopted transformation to be applied on the degraded image pixels, comparisons are done for both grey-level mapping and local/global transformation techniques.

4.1. Comparison to the genetic algorithm

The obtained results have been compared qualitatively, Fig. 5, and numerically, Table 1, to those obtained in [6]. So, the same

Table 1
Comparison between PSNR values for the AG [6] and the proposed ABC.

Input image	GA proposed in [6]	The proposed ABC
gr1	14.16	**23.64**
gr2	**13.21**	12.18
gr3	13.75	**17.42**
gr4	20.12	**20.16**
gr5	17.92	**24.84**

parameters are used, as far as the number of objective function evaluations and the number of iterations are concerned. Thus, the number of solutions is chosen to be 25, it is the same number of the employed bees and the onlookers, while the number of iterations is set to 10.

For what is specific to the ABC algorithm, the threshold of activation of scouts *limit* is set to 5; so, the solutions which have been inactive for more than 5 generations tend to be replaced with new randomly generated ones.

Fig. 5 shows the results obtained from the application of the proposed ABC algorithm on a set of degraded images, and their comparisons with the results obtained in [6]. The figure shows from left to right, the instances of input images, the results of [6], and our results. It is clear from the figure that the proposed approach has successfully improved the input images. The histograms corresponding to input images and those of their enhanced equivalents are presented in Fig. 6, from left to right: input images, their histograms, enhanced images and their histograms. It is well seen from the histograms of the output images that the grey levels have become more stretched, over the interval [0, 255], which proves the efficiency of the proposed approach.

When comparing our results to those of Hashemi et al. [6] (Fig. 5), we see that the results of both algorithms are visually almost the same. So, a numerical comparison seems to be necessary here. The PSNR (Peak Signal to Noise Ratio) between the input and output images is used to compare the enhancements of the genetic algorithm of [6] and that given using our approach, this is given in Table 1. As seen from the table, the proposed approach has given better results in 4 out of 5 cases, which proves its superiority.

Fig. 7 presents the result of using the proposed ABC for enhancing a scanned image of a book page. As seen from the image, the algorithm really succeeds in enhancing the quality of the input image, Fig. 7(a); and offers a more readable version of the book page, Fig. 7(b).

In addition to its application on grey-level images, the proposed approach has been extended to enhance colour images. Here, the RGB (Red, Green, Blue) space is considered. In the case of colour images, the algorithm is applied on the three channels of colours separately by considering each channel as a grey-level image. Then, the results obtained from enhancing each of the three channels will be integrated to form the resulting colour image. Fig. 8 gives some examples, where we find that all degraded images, on the left, have been considerably enhanced, on the right.

4.2. Comparison to the Cuckoo Search algorithm

Recently, new contrast enhancement techniques have emerged; not only a multitude of optimisation approaches, but also more than one transformation techniques have been used. In addition to the grey-level mapping transformation, explained above, the so-called local/global transformation is widely used in the literature [3,4,10].

As far as the grey-level mapping technique is concerned the only work present in the literature is that of Hashemi et al. [6] using a genetic algorithm. Related comparisons have been presented above. For the case of comparison with regard to the transformation to be used, we have implemented further comparisons. First the ABC proposed in the paper has been adapted to the local/global transformation described and used in [3,4,10,5], and then compared with the Cuckoo Search approach proposed in [5], using the same parameter settings. Second, we implemented the Cuckoo Search algorithm using the grey-level mapping technique, adopted as a basic transformation in the present work, and compared it to the proposed ABC.

4.2.1. Comparisons for local/global transformation

The local/global transformation [3,4,10] changes the pixel intensity values of the input image according to the formula given in Eq. (7) to enhance the input degraded image. In the equation, $f(i,j)$ is the intensity of the input image, $m(i,j)$ is the grey level local mean, $\sigma(i,j)$ is the grey level local standard deviation, D is the global mean intensity of the whole image, $g(i,j)$ is the output intensity and a, b, c and d are four parameters:

$$g(i,j) = \left[d \cdot \frac{D}{\sigma(i,j)+b}\right] \cdot [f(i,j) - c.m(i,j)] + m(i,j)^a \tag{7}$$

As stated above, we implemented the ABC according to the same process given in the chart of Fig. 4 with the specificity of looking for the best values of the parameters a, b, c and d instead of the set of grey levels. On the other hand, the Cuckoo Search algorithm proposed by Agrawal and Panda in [5] with the same parameters is used in the following for comparison purposes.

Five metrics, basically used in [5,6], are used in the following to statistically compare between the results of the two approaches: the objective function value, the entropy, the Feature Similarity Index (FSIM), the number of Sobel edges and the PSNR. Every algorithm has been executed 10 independent times for each image. The images that have been used in these comparisons are those already used above, they are composed of five grey-level images and four colour images.

The other parameters of the two algorithms are set as follows. The population size (number of nests) is set to 15, the number of generations is chosen to be 25, the probability of discovering an alien solution in the case of CS is 0.01, and finally, the parameter *limit* of the ABC algorithm is set to 20.

As far as the ranges of the parameters a, b, c and d, used in the transformation of Eq. (7), are concerned; we used the same ranges as in [4], where the authors use the following ranges: $a \in [0, 1.5]$, $b \in [1, D/2]$, $c \in [0, 1]$ and $d \in [0.5, 1.5]$; where D is the mean intensity of the input image. Other works generally use the range [0, 0.5] for the second parameter b, but as mentioned in [4], this interval, even if it permits reinforcing edges, it gives discretised result images, as seen in Fig. 9.

Tables 2–6 show the comparisons, of all five metrics, for the case of grey-level images between the two algorithms in terms of the best, worst, median, mean and standard deviation values obtained over the 10 runs. From the tables, its is clear that the proposed ABC outperforms the Cuckoo Search algorithm, as seen in the table of fitness comparison, the mean value over all ten runs is always higher for the ABC, presented in bold.

In addition to succeeding in optimising the objective function, the proposed ABC algorithm has also been better in improving the entropy value, improving the latter has well contributed in improving the fitness quality, as seen in Eq. (5).

When comparing colour images, Tables 7–11, we opted for using for each metric the mean value of the measures gotten from each colour channel. As seen from the tables, again, the ABC outperformed the CS in terms of mean fitness and entropy values.

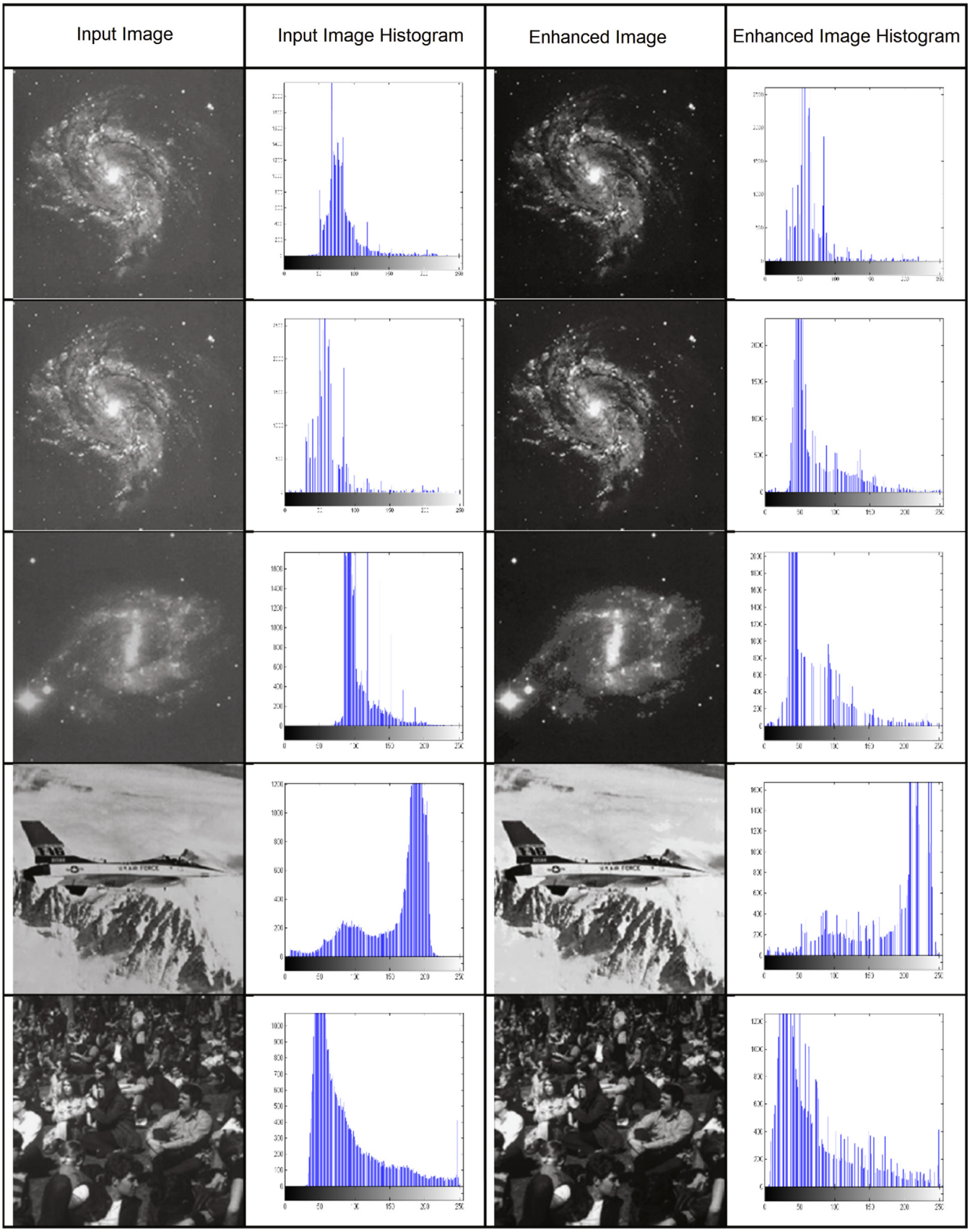

Fig. 6. A histogram-based evaluation of the proposed approach.

a

The use of a vault and of concrete enabled the Romans to build the huge dome of the Pantheon, which is over 140 feet in diameter, and about 157 feet in height.

viaduct ['vaiədʌkt] - виадукт <- via (lat.) - път; duco (lat.) - водя
unlike - за разлика от
outstanding - изтъкнат
whereas [wəz'æz] - докато; от друга страна
effect of massiveness - по-скоро ефект на масивност, отколкото
rather than of grace на изящност
elaborate [i'læbərit]- сложен, подробен, претрупан, претенциозен
delicacy ['delikəsi] - изтънченост, изящество, финес
to lack [læk] - липсва ми; не ми достига; лишен съм от;
to resemble [ri'zembl]- приличам на
to enable [i'neibl] - давам възможност на

Exercises

I. Choose a preposition from those in brackets to fill in the blanks: (*of, by, for,to, in*)

It was possible --- the Romans to construct tall buildings.

They used the arch --- their bridges and --- the walls --- their structures.

The Greek orders were often used --- decoration only.

The exterior --- the Roman building gave the effect --- massiveness.

Concrete and vaults were used --- constructing domes.

The Colosseum was about 157 feet --- height.

The Composite order was formed --- combining the Ionic and the Corinthian.

The Roman combined the different orders, giving stability --- the building.

The column is employed as a support --- a weight above.

--- ornamenting the capitals, the Romans made even more beautiful.

II. Translate into Bulgarian with the help of a dictionary:

The thermae were the focal points of social life. The Diocletian thermae in Rome were situated in a huge park and could accommodate 3000 bathers. They were rectangular in plan and comprised halls, vestibules, and courtyards, arranged symmetrically about a cross-axis. Leading from the central hall on the short cross-axis was the tepidarium, or medium-temperature bath. The caladarium, or hot bath, projected out from the long side of the building. Opposite to the caladarium was the open-air cold pool, or frigidarium. There were also gymnasiums equipped with devices for games and exercises. Beneath the thermae were the boiler rooms.

UNIT 3

ARCHITECTURE OF THE BULGARIAN NATIONAL REVIVAL

The Bulgarian National Revival is the period of rapid economic, cultural, and political development which culminates in the liberation struggle against Ottoman rule. During that period, which started in the middle of the 18th c., new towns emerged and, together with a number of old towns, grew into important centers of the crafts, manufacture, commerce, and culture.

b

The use of a vault and of concrete enabled the Romans to build the huge dome of the Pantheon, which is over 140 feet in diameter, and about 157 feet in height.

viaduct ['vaiədʌkt] - виадукт <- via (lat.) - път; duco (lat.) - водя
unlike - за разлика от
outstanding - изтъкнат
whereas [wəz'æz] - докато; от друга страна
effect of massiveness - по-скоро ефект на масивност, отколкото
rather than of grace на изящност
elaborate [i'læbərit]- сложен, подробен, претрупан, претенциозен
delicacy ['delikəsi] - изтънченост, изящество, финес
to lack [læk] - липсва ми; не ми достига; лишен съм от;
to resemble [ri'zembl]- приличам на
to enable [i'neibl] - давам възможност на

Exercises

I. Choose a preposition from those in brackets to fill in the blanks: (*of, by, for,to, in*)

It was possible --- the Romans to construct tall buildings.

They used the arch --- their bridges and --- the walls --- their structures.

The Greek orders were often used --- decoration only.

The exterior --- the Roman building gave the effect --- massiveness.

Concrete and vaults were used --- constructing domes.

The Colosseum was about 157 feet --- height.

The Composite order was formed --- combining the Ionic and the Corinthian.

The Roman combined the different orders, giving stability --- the building.

The column is employed as a support --- a weight above.

--- ornamenting the capitals, the Romans made even more beautiful.

II. Translate into Bulgarian with the help of a dictionary:

The thermae were the focal points of social life. The Diocletian thermae in Rome were situated in a huge park and could accommodate 3000 bathers. They were rectangular in plan and comprised halls, vestibules, and courtyards, arranged symmetrically about a cross-axis. Leading from the central hall on the short cross-axis was the tepidarium, or medium-temperature bath. The caladarium, or hot bath, projected out from the long side of the building. Opposite to the caladarium was the open-air cold pool, or frigidarium. There were also gymnasiums equipped with devices for games and exercises. Beneath the thermae were the boiler rooms.

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Fig. 7. Text image enhancement with the proposed approach. (a) Input scanned book page. (b) Output enhanced image.

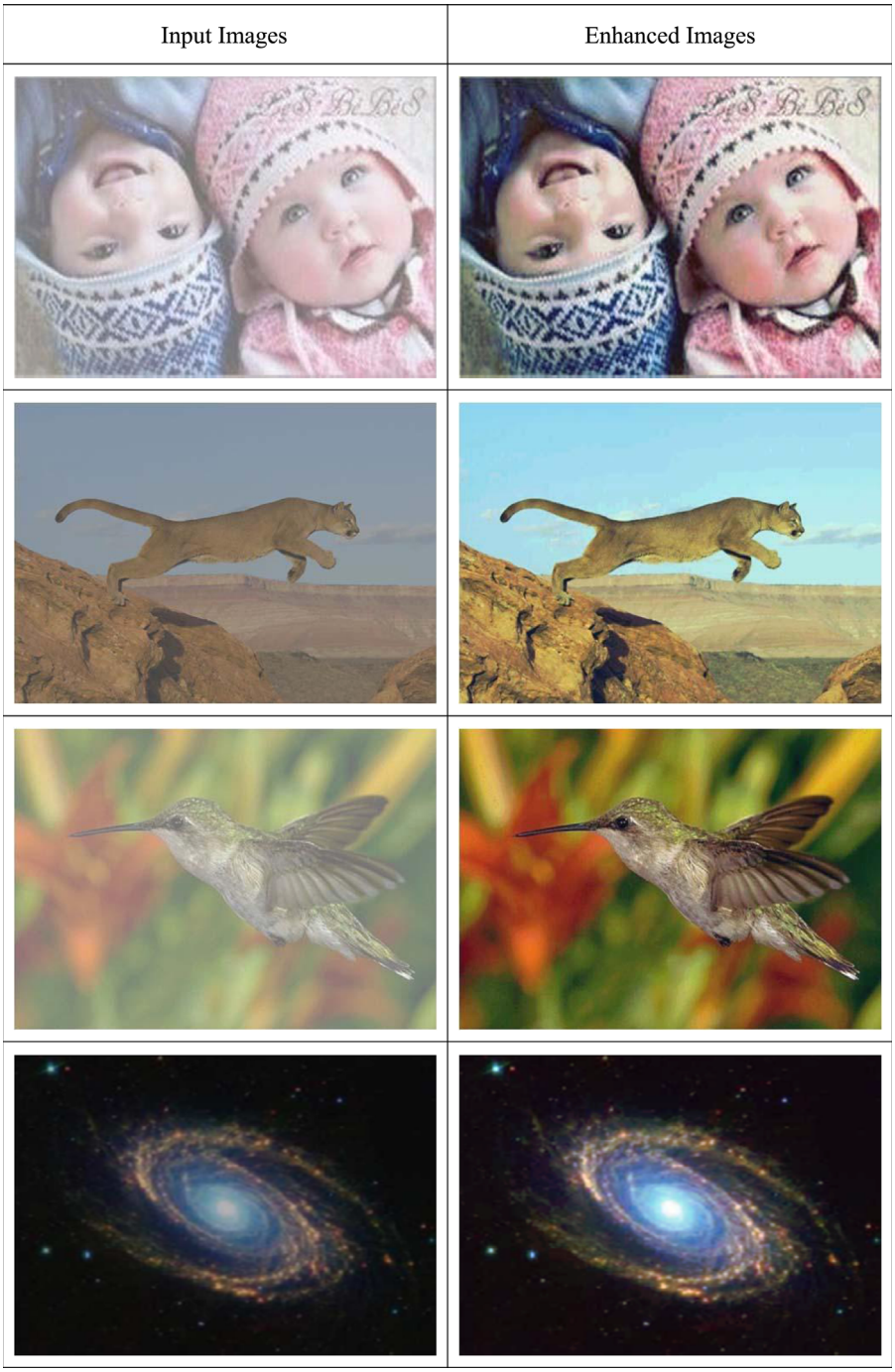

Fig. 8. Colour image enhancement with the proposed ABC algorithm.

4.2.2. Comparisons for grey-level mapping

In addition to comparing the proposed ABC against the GA, we compare it here with the Cuckoo Search algorithm using the same parameters of the CS used above; but here with using the grey-level mapping transformation. Tables 12–16 and Tables 17–21 summarise the obtained results for grey-level and colour images respectively. The same metrics – fitness, FSIM, PSNR, entropy and number of edges – are used.

From the tables, it is obvious that the proposed ABC is better than the CS algorithm in terms of the fitness value and the entropy.

As in previous comparisons; we opted for the case of colour images, for using for each metric the mean value of the measures got from each colour channel. As seen from Tables 17–21, the ABC algorithm, again, outperformed the CS algorithm in terms of mean fitness and entropy values.

In addition, to its superiority in terms of mean values of fitness and entropy, we remark that the proposed ABC has given better values of the best, median and even worst values obtained over ten runs in the majority of cases. The worst obtained values of fitness and entropy outperformed in many cases the mean values got by the CS algorithm.

4.2.3. Critics of the local/global transformation

As seen in the above-presented tables, the proposed ABC outperformed the CS algorithm and the GA algorithm for both types of

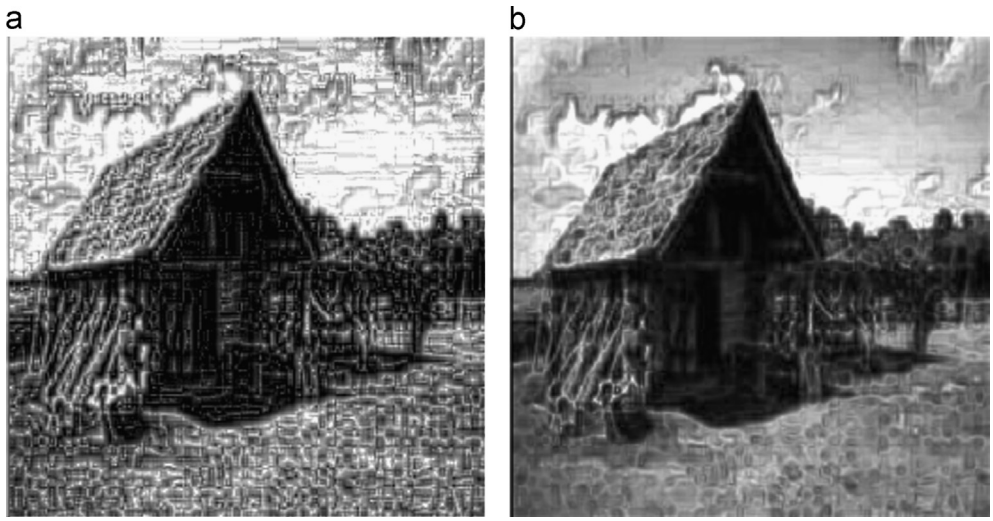

Fig. 9. The impact of the range of parameter b on image quality. (a) $b \in (0, 0.5)$. (b) $b \in (1, D/2)$.

Table 2
Comparing fitness values for ABC and CS algorithms for grey-level images using the local/global transformation.

Image	ABC Algorithm					Cuckoo Search				
	Best	Worst	Median	Mean	STD	Best	Worst	Median	Mean	STD
gr1	21.334	20.784	21.208	**21.165**	0.156	21.164	19.289	20.225	20.202	0.602
gr2	21.270	20.092	20.916	**20.850**	0.350	20.956	18.353	19.104	19.461	0.995
gr3	21.454	19.284	20.966	**20.807**	0.714	20.370	18.376	19.347	19.406	0.755
gr4	21.382	21.075	21.277	**21.281**	0.095	21.242	19.678	20.731	20.700	0.482
gr5	21.088	20.840	20.979	**20.965**	0.087	20.895	19.754	20.241	20.313	0.333

Table 3
Comparing entropy values for ABC and CS algorithms for grey-level images using the local/global transformation.

Image	ABC Algorithm					Cuckoo Search				
	Best	Worst	Median	Mean	STD	Best	Worst	Median	Mean	STD
gr1	7.725	7.506	7.678	7.658	0.063	7.660	6.961	7.352	7.324	0.214
gr2	7.666	7.273	7.554	7.513	0.125	7.590	6.565	6.878	7.014	0.376
gr3	7.740	6.939	7.594	7.506	0.268	7.311	6.621	6.995	6.996	0.252
gr4	7.700	7.567	7.650	7.652	0.040	7.632	7.118	7.458	7.438	0.169
gr5	7.649	7.560	7.610	7.605	0.028	7.567	7.198	7.378	7.389	0.121

Table 4
Comparing PSNR values for ABC and CS algorithms for grey-level images using the local/global transformation.

Image	ABC Algorithm					Cuckoo Search				
	Best	Worst	Median	Mean	STD	Best	Worst	Median	Mean	STD
gr1	14.808	11.765	13.089	13.164	0.788	17.822	12.370	13.861	14.246	1.712
gr2	17.376	10.253	11.436	12.203	2.229	19.510	8.049	12.604	13.819	3.605
gr3	13.237	10.791	12.044	12.174	0.786	19.817	8.020	10.771	12.114	3.969
gr4	18.312	13.674	16.952	16.802	1.238	18.627	14.367	17.230	16.985	1.259
gr5	14.394	10.516	11.967	12.202	1.060	18.259	11.012	13.431	14.280	2.490

transformation; the grey-level mapping technique and the local/global transformation. Figs. 10 and 11 give some qualitative comparisons between the two optimisers using the two types of transformation applied on grey level and colour images respectively.

From the figures, the superiority of the ABC approach using the grey-level mapping transformation is clear, then comes the CS using the same technique. The other two algorithms give some unnatural-looking images; the discretisation is always there even when we used the new ranges of the parameter b [4].

We also see from the same figures that though the ABC and CS algorithms give better fitness value when using the local/global transformation, if compared to their counterparts with the grey-level

Table 5
Comparing numbers of edges for ABC and CS algorithms for grey-level images using the local/global transformation.

Image	ABC Algorithm					Cuckoo Search				
	Best	Worst	Median	Mean	STD	Best	Worst	Median	Mean	STD
gr1	1.33E+03	5.33E+02	9.99E+02	9.98E+02	2.64E+02	1.76E+03	9.57E+02	1.37E+03	1.38E+03	2.75E+02
gr2	2.90E+03	1.30E+03	2.15E+03	2.10E+03	4.91E+02	3.08E+03	1.25E+03	2.44E+03	2.40E+03	5.87E+02
gr3	2.17E+03	1.15E+03	1.56E+03	1.65E+03	3.06E+02	2.03E+03	9.54E+02	1.73E+03	1.67E+03	3.38E+02
gr4	3.53E+03	1.84E+03	3.16E+03	3.08E+03	4.91E+02	3.95E+03	2.92E+03	3.36E+03	3.31E+03	2.91E+02
gr5	2.56E+03	8.90E+02	1.88E+03	1.87E+03	5.59E+02	3.02E+03	1.67E+03	2.60E+03	2.43E+03	5.74E+02

Table 6
Comparing FSIM values for ABC and CS algorithms for grey-level images using the local/global transformation.

Image	ABC Algorithm					Cuckoo Search				
	Best	Worst	Median	Mean	STD	Best	Worst	Median	Mean	STD
gr1	0.521	0.419	0.466	0.469	0.030	0.658	0.484	0.559	0.567	0.057
gr2	0.576	0.380	0.427	0.445	0.057	0.728	0.405	0.568	0.557	0.112
gr3	0.623	0.305	0.376	0.405	0.095	0.805	0.262	0.477	0.492	0.160
gr4	0.738	0.564	0.663	0.661	0.047	0.849	0.674	0.706	0.741	0.068
gr5	0.661	0.538	0.592	0.594	0.032	0.872	0.577	0.665	0.673	0.096

Table 7
Comparing fitness values for ABC and CS algorithms for colour images using the local/global transformation using the local/global transformation.

Image	ABC Algorithm					Cuckoo Search				
	Best	Worst	Median	Mean	STD	Best	Worst	Median	Mean	STD
c1	21.506	20.790	21.221	**21.205**	0.199	20.779	19.867	20.360	20.319	0.299
c2	18.256	17.389	17.946	**17.927**	0.245	17.270	16.432	16.794	16.852	0.293
c3	20.382	18.101	19.042	**19.047**	0.744	18.125	16.755	17.280	17.321	0.375
c4	18.773	18.619	18.701	**18.704**	0.041	18.232	17.754	17.975	17.984	0.132

Table 8
Comparing entropy values for ABC and CS algorithms for colour images using the local/global transformation.

Image	ABC Algorithm					Cuckoo Search				
	Best	Worst	Median	Mean	STD	Best	Worst	Median	Mean	STD
c1	7.704	7.416	7.587	7.585	0.080	7.450	7.085	7.273	7.259	0.113
c2	7.052	6.708	6.923	6.917	0.097	6.655	6.327	6.526	6.513	0.114
c3	7.292	6.445	6.790	6.800	0.282	6.487	5.975	6.180	6.186	0.138
c4	7.099	7.041	7.074	7.074	0.015	6.926	6.766	6.847	6.845	0.042

Table 9
Comparing PSNR values for ABC and CS algorithms for colour images using the local/global transformation.

Image	ABC Algorithm					Cuckoo Search				
	Best	Worst	Median	Mean	STD	Best	Worst	Median	Mean	STD
c1	14.028	12.852	13.505	13.496	0.403	15.425	12.131	13.471	13.623	1.009
c2	12.769	11.294	11.866	11.990	0.495	17.538	10.669	12.757	13.438	2.090
c3	17.264	10.939	14.776	14.491	1.826	21.973	15.289	18.572	18.622	2.134
c4	8.085	7.180	7.814	7.749	0.262	12.187	6.645	10.237	9.835	1.797

Table 10
Comparing numbers of edges for ABC and CS algorithms for colour images using the local/global transformation.

Image	ABC Algorithm					Cuckoo Search				
	Best	Worst	Median	Mean	STD	Best	Worst	Median	Mean	STD
c1	3.47E+03	2.74E+03	3.12E+03	3.14E+03	2.20E+02	3.59E+03	2.82E+03	3.41E+03	3.31E+03	2.46E+02
c2	4.66E+03	3.61E+03	3.99E+03	4.06E+03	3.68E+02	4.06E+03	3.30E+03	3.71E+03	3.68E+03	2.67E+02
c3	4.48E+03	3.36E+03	3.99E+03	3.98E+03	3.41E+02	3.62E+03	2.37E+03	3.16E+03	3.08E+03	3.92E+02
c4	2.15E+03	1.97E+03	2.05E+03	2.06E+03	6.02E+01	2.76E+03	2.32E+03	2.43E+03	2.52E+03	1.80E+02

Table 11
Comparing FSIM values for ABC and CS algorithms for colour images using the local/global transformation.

Image	ABC Algorithm					Cuckoo Search				
	Best	Worst	Median	Mean	STD	Best	Worst	Median	Mean	STD
c1	0.624	0.419	0.499	0.500	0.058	0.790	0.556	0.655	0.661	0.067
c2	0.600	0.408	0.475	0.482	0.051	0.789	0.554	0.622	0.648	0.075
c3	0.708	0.339	0.542	0.517	0.136	0.882	0.647	0.816	0.799	0.071
c4	0.370	0.348	0.358	0.357	0.006	0.499	0.394	0.440	0.444	0.040

Table 12
Comparing fitness values for ABC and CS algorithms for grey-level images using grey-level mapping.

Image	ABC Algorithm					Cuckoo Search				
	Best	Worst	Median	Mean	STD	Best	Worst	Median	Mean	STD
gr1	14.373	14.015	14.160	**14.178**	0.093	14.145	14.038	14.113	14.105	0.029
gr2	13.961	13.591	13.694	**13.713**	0.109	13.760	13.492	13.675	13.667	0.086
gr3	14.905	14.438	14.617	**14.648**	0.161	14.769	14.351	14.581	14.573	0.132
gr4	16.793	16.380	16.567	**16.589**	0.117	16.744	16.437	16.570	16.587	0.093
gr5	17.100	16.833	17.010	**16.993**	0.090	17.087	16.793	16.867	16.896	0.091

Table 13
Comparing entropy values for ABC and CS algorithms for grey-level images using grey-level mapping.

Image	ABC Algorithm					Cuckoo Search				
	Best	Worst	Median	Mean	STD	Best	Worst	Median	Mean	STD
gr1	5.230	5.111	5.161	5.166	0.031	5.174	5.122	5.150	5.148	0.016
gr2	5.117	4.991	5.021	5.033	0.039	5.052	4.955	5.011	5.016	0.031
gr3	5.443	5.278	5.360	5.371	0.062	5.404	5.265	5.345	5.341	0.045
gr4	6.030	5.871	5.940	5.948	0.046	6.006	5.889	5.941	5.945	0.035
gr5	6.248	6.143	6.216	6.209	0.035	6.254	6.128	6.165	6.171	0.036

Table 14
Comparing PSNR values for ABC and CS algorithms for grey-level images using grey-level mapping.

Image	ABC Algorithm					Cuckoo Search				
	Best	Worst	Median	Mean	STD	Best	Worst	Median	Mean	STD
gr1	23.016	17.038	18.494	18.914	1.651	21.462	14.363	17.821	17.517	1.983
gr2	15.112	13.037	14.141	14.008	0.779	15.548	13.160	13.679	13.971	0.769
gr3	18.091	13.719	15.110	15.773	1.567	17.666	14.483	15.828	15.889	1.225
gr4	26.618	19.273	21.251	21.874	2.482	23.618	18.227	21.255	21.116	1.674
gr5	34.856	25.638	27.905	29.026	3.078	37.357	23.449	30.488	30.624	4.319

Table 15
Comparing numbers of edges for ABC and CS algorithms for grey-level images using grey-level mapping.

Image	ABC Algorithm					Cuckoo Search				
	Best	Worst	Median	Mean	STD	Best	Worst	Median	Mean	STD
gr1	1.74E+03	1.32E+03	1.48E+03	1.52E+03	1.45E+02	1.67E+03	1.37E+03	1.50E+03	1.51E+03	9.83E+01
gr2	2.49E+03	1.92E+03	2.03E+03	2.08E+03	1.60E+02	2.45E+03	2.06E+03	2.19E+03	2.19E+03	1.15E+02
gr3	1.78E+03	1.39E+03	1.61E+03	1.60E+03	1.25E+02	1.81E+03	1.32E+03	1.54E+03	1.53E+03	1.32E+02
gr4	3.00E+03	2.82E+03	2.88E+03	2.90E+03	6.40E+01	2.92E+03	2.84E+03	2.88E+03	2.88E+03	3.13E+01
gr5	3.05E+03	2.61E+03	2.84E+03	2.82E+03	1.47E+02	2.94E+03	2.64E+03	2.80E+03	2.78E+03	8.54E+01

mapping technique; they could not give really natural-looking images. The obtained images are either showing some dicretisation or not well enhanced, as far as contrast is concerned. Hence, introducing the entropy in the objective function equation is not enough in the case of using the local/global transformation, even if it allows good convergence of the algorithm. As a result, the grey-mapping approach is quite better in enhancing the contrast with guaranteeing at the same time the preservation of the image natural looking.

As additional drawbacks of the local/global transformation, we cite the following. First, setting the ranges of the parameters a, b, c

Table 16
Comparing FSIM values for ABC and CS algorithms for grey-level images using grey-level mapping.

Image	ABC Algorithm					Cuckoo Search				
	Best	Worst	Median	Mean	STD	Best	Worst	Median	Mean	STD
gr1	0.924	0.862	0.898	0.896	0.020	0.912	0.891	0.901	0.902	0.007
gr2	0.974	0.923	0.946	0.945	0.016	0.957	0.900	0.933	0.932	0.016
gr3	0.936	0.885	0.908	0.909	0.015	0.926	0.891	0.897	0.902	0.013
gr4	0.990	0.975	0.981	0.982	0.005	0.991	0.977	0.985	0.984	0.004
gr5	0.992	0.980	0.988	0.988	0.004	0.993	0.981	0.988	0.988	0.004

Table 17
Comparing fitness values for ABC and CS algorithms for colour images using grey-level mapping.

Image	ABC Algorithm					Cuckoo Search				
	Best	Worst	Median	Mean	STD	Best	Worst	Median	Mean	STD
c1	17.325	17.183	17.274	**17.267**	0.041	17.212	17.123	17.155	17.159	0.028
c2	13.223	13.071	13.139	**13.143**	0.045	13.143	13.040	13.096	13.093	0.032
c3	15.403	15.285	15.320	**15.331**	0.044	15.283	15.136	15.244	15.233	0.045
c4	13.671	13.450	13.551	**13.560**	0.066	13.612	13.379	13.519	13.515	0.059

Table 18
Comparing entropy values for ABC and CS algorithms for colour images using grey-level mapping.

Image	ABC Algorithm					Cuckoo Search				
	Best	Worst	Median	Mean	STD	Best	Worst	Median	Mean	STD
c1	6.207	6.151	6.184	6.182	0.016	6.168	6.131	6.143	6.145	0.011
c2	5.465	5.413	5.427	5.432	0.017	5.428	5.395	5.415	5.416	0.010
c3	5.587	5.544	5.564	5.566	0.014	5.546	5.495	5.534	5.529	0.016
c4	5.347	5.279	5.309	5.314	0.021	5.312	5.250	5.292	5.291	0.017

Table 19
Comparing PSNR values for ABC and CS algorithms for colour images using grey-level mapping.

Image	ABC Algorithm					Cuckoo Search				
	Best	Worst	Median	Mean	STD	Best	Worst	Median	Mean	STD
c1	15.655	14.288	15.066	14.989	0.501	15.775	14.506	15.224	15.186	0.501
c2	17.956	14.038	14.873	15.172	1.122	16.536	14.662	15.961	15.775	0.650
c3	12.546	10.192	10.918	11.008	0.683	11.319	10.455	10.942	10.937	0.293
c4	24.033	21.427	23.005	22.778	0.983	23.255	20.383	22.017	21.826	1.061

Table 20
Comparing numbers of edges for ABC and CS algorithms for colour images using grey-level mapping.

Image	ABC Algorithm					Cuckoo Search				
	Best	Worst	Median	Mean	STD	Best	Worst	Median	Mean	STD
c1	3.38E+03	3.27E+03	3.31E+03	3.32E+03	3.59E+01	3.46E+03	3.19E+03	3.31E+03	3.32E+03	8.90E+01
c2	2.71E+03	2.26E+03	2.47E+03	2.48E+03	1.46E+02	2.76E+03	2.35E+03	2.53E+03	2.52E+03	1.36E+02
c3	2.57E+03	2.34E+03	2.51E+03	2.48E+03	7.63E+01	2.70E+03	2.40E+03	2.53E+03	2.52E+03	8.76E+01
c4	2.03E+03	1.87E+03	1.93E+03	1.93E+03	5.07E+01	1.98E+03	1.85E+03	1.94E+03	1.93E+03	3.45E+01

Table 21
Comparing FSIM values for ABC and CS algorithms for colour images using grey-level mapping.

Image	ABC Algorithm					Cuckoo Search				
	Best	Worst	Median	Mean	STD	Best	Worst	Median	Mean	STD
c1	0.773	0.742	0.762	0.761	0.010	0.777	0.752	0.763	0.763	0.007
c2	0.865	0.824	0.850	0.847	0.015	0.862	0.829	0.849	0.846	0.011
c3	0.891	0.852	0.870	0.870	0.012	0.877	0.849	0.864	0.864	0.009
c4	0.961	0.939	0.948	0.950	0.009	0.959	0.929	0.945	0.945	0.010

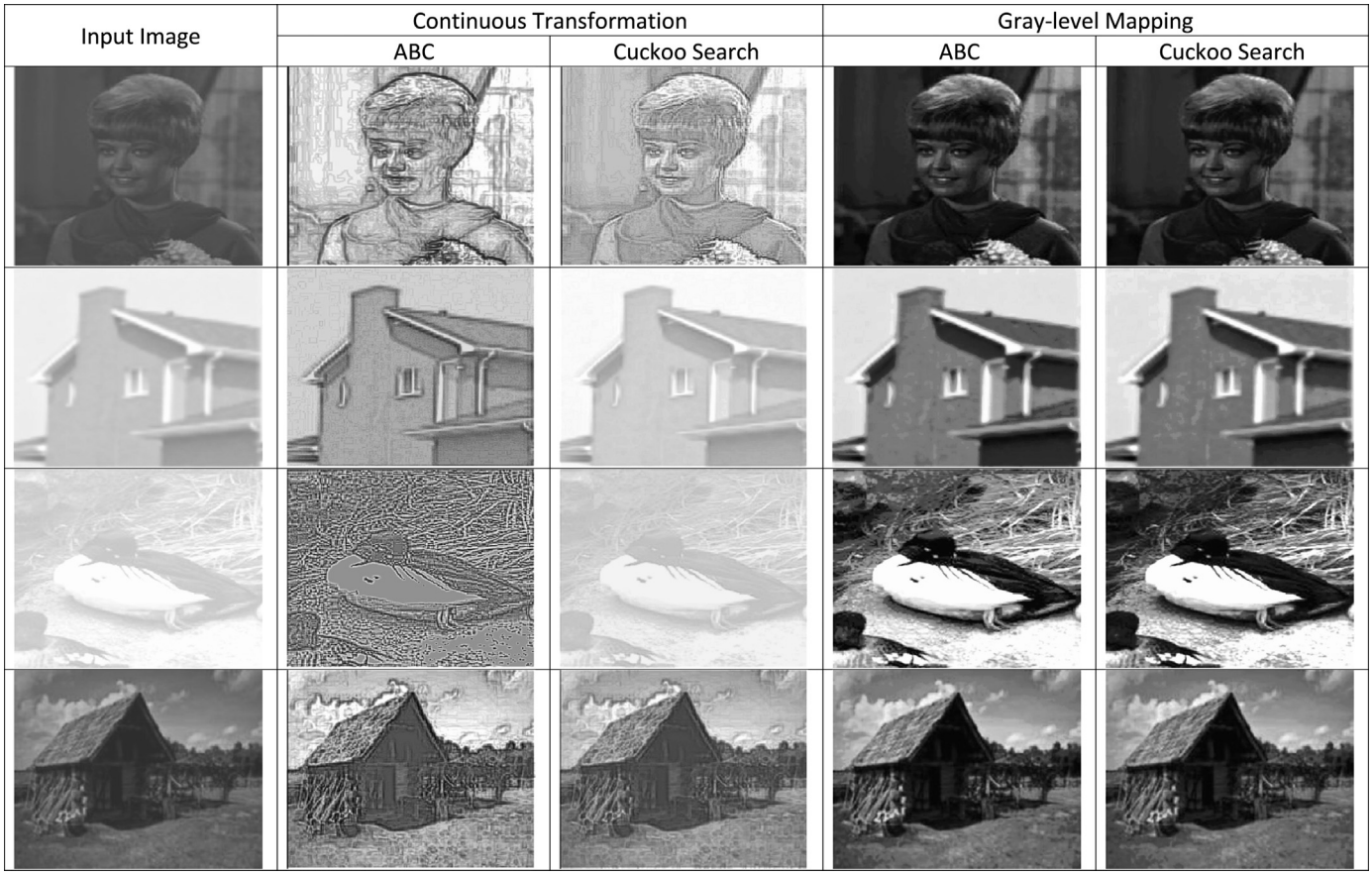

Fig. 10. Comparison between different transformations for the ABC and the CS applied on grey level images.

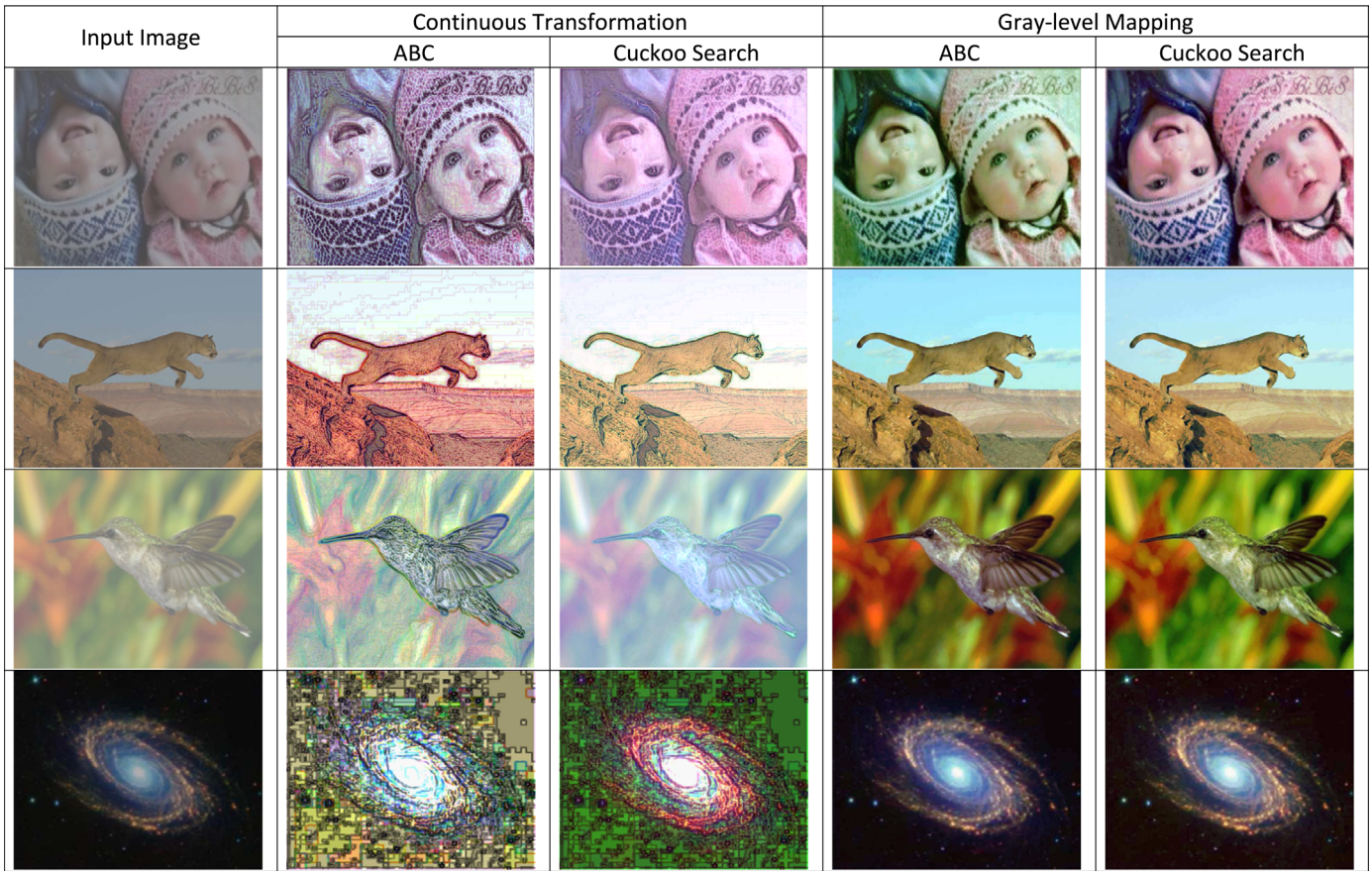

Fig. 11. Comparison between different transformations for the ABC and the CS applied on colour images.

and d used in the transformation remains an unsolved issue, there is no consensus about the best values of these parameters in the literature. Second, the window size of both the mean and standard deviation used in the transformation is another parameter to be set. Finally, calculating the latter values, local mean and standard deviation, would lead to an extra algorithmic complexity.

5. Conclusion

In this paper an artificial bee colony algorithm has been used for image contrast enhancement. The grey levels of the input image are replaced by a new set of grey levels. The latter is looked for using an ABC search process. The proposed approach has been tested on a set of input images and proved to be better than conventional metaheuristics. The obtained results have been compared to those found by a genetic algorithm [6], which itself, according to [6], outperforms other conventional techniques: grey-level grouping, adaptive grey-level grouping, and histogram equalisation. In four out of five cases, the proposed ABC outperformed the genetic algorithm [6].

In addition to its use in enhancing grey-level images, the proposed algorithm has been extended to deal with colour images. In the case of a colour images, the grey levels corresponding to the three colour channels of the input image are separately enhanced, then the results gotten from enhancing each channel are recombined to form the output image. The algorithm has proved its ability to enhance colour images through its application on a set of degraded colour images.

For better validation of the proposed approach, two further comparisons to a recently proposed metaheuristic, the Cuckoo Search algorithm, have been done. First, the proposed ABC has been adapted to the so-called local/global transformation to be able to compare it to the work of Agrawal et al. [5] where a CS algorithm is used as an optimiser; then, our results have been compared to the same CS algorithm. The best, worst, median, mean and standard deviation values of the chosen quality metrics over ten independent runs for each image of the set of test images have been compared. Second, the proposed ABC and CS algorithms have been compared against each other using the grey-level mapping technique, adopted in the paper. Quantitative and qualitative results have proved the superiority of the proposed ABC for image contrast enhancement.

As future work, two extensions of the present work are planned. First, the use of the HSV (Hue, Saturation, Value) space for the case of colour images would be more appropriate: it would offer genuine colours to natural scenes. In this case only the value component of the HSV format is to be enhanced, this also makes it possible to reduce execution time. Second, we plan to apply other variants of the ABC algorithm to solve the same enhancement problem.

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