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A quality guaranteed robust image watermarking optimization with Artificial Bee Colony

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ABSTRACT

Achieving robustness with a limited distortion level is a challenging design problem for watermarking systems in multimedia applications with a guaranteed quality requirement. In this paper, we provide an intelligent system for watermarking through incorporating a meta-heuristic technique along with an embedding method to achieve an optimized performance. The optimization objective is to provide the maximum possible robustness without exceeding a predetermined distortion limit. Hence, the quality level of the watermarking method could be guaranteed through that constraint optimization. A new fitness function is defined to provide the required convergence toward the optimum solution for the defined optimization problem. The fitness function is based on dividing its applied solution population into two groups, where each group is ranked according to a different objective. Thus, the multi-objectives in the problem are decoupled and solved through two single-objective sub-problems. Unlike existing watermarking optimization techniques, the proposed work does not require weighting factors. To illustrate the effectiveness of the proposed approach, we employ a recent watermarking technique, and then use it as the embedding method to be optimized. The Artificial Bee Colony is selected as the meta-heuristic optimization method in which the proposed fitness function is used. Experimental results show that the imposed quality constraint is satisfied, and that the proposed method provides enhanced robustness under different attacks for various quality thresholds. The presented approach offers a robust solution that can be applied to numerous multimedia applications such as film industry, intelligent surveillance and security systems.

1. Introduction

The widespread use of the internet has made the multimedia information easy to be shared and accessed. Hence, valuable data could be exposed to malicious manipulations or violation of intellectual property rights. Digital watermarking is one of the most popular ways for securing multimedia data over a shared medium. It has been the core of many applications such as: copyright protection, copy control, authentication, broadcast monitoring, ownership identification, and tamper detection (Fung, Gortan, & Godoy Jr, 2011; Husain, 2012; Liu & He, 2005; Olanrewaju, Khalifa, Hashim, Zeki, & Aburas, 2011; Preda & Vizireanu, 2010; Yusof & Khalifa, 2007). Watermarking is the process of embedding digital information, called the watermark, inside a cover digital content such as: image, video, audio, or text (Cox, Miller, Bloom, & Honsinger, 2002).

In robust watermarking design, it is challenging to achieve robustness along with high quality due to their conflict behavior with each other. The robustness is essential for many applications, while the quality is necessary for any watermarking method. However, applications may differ in their required quality level. Meta-heuristic optimization techniques can be utilized to search for embedding parameters that provide the best compromise between robustness and quality.

A meta-heuristic is an iterative process, which intelligently searches for the optimum solution inside a search space that contains all feasible solutions to an optimization problem. It must define a fitness function that measures the quality of any solution according to the design objectives. For multi-objective optimization problems, the fitness function is evaluated by measuring all objective functions. Then, a multi-objective optimization method is applied to rank the solutions, selected per iteration, according to their measured objectives (J. Wang, Peng, & Shi, 2011).

Existing work on watermarking optimization is versatile. Some existing watermarking optimization methods focus on optimizing a single objective only, and the other objectives are obtained

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through predetermined or adaptively evaluated embedding parameters. Farhan and Bilal (2011) introduced an optimized robust embedding technique in the wavelet domain. The quality was optimized by searching for the optimum locations, where coefficients were modified according to the watermark. Hence, the fitness function was evaluated based on the quality objective only, while the robustness was managed by a fixed embedding strength. The authors presented the quality performance only, but no attacks were considered for robustness evaluation.

Hammouri, Alrifai, and Al-Hiary (2013) proposed a watermarking scheme based on a meta-heuristic optimization method. The embedding was applied in the Discrete Wavelet Transform (DWT) domain. The optimum embedding positions were selected to enhance the robustness of the watermark against some of the common attacks. Thus, the authors represented the fitness of the solution by its achieved robustness, while the quality objective was considered by the embedding strength parameters that were evaluated adaptively.

To improve the performance of watermarking, both robustness and quality should be optimized. That is, we have a multi-objective optimization problem. Many existing methods (Ali, Ahn, & Siarry, 2014; Aslantas, 2009; Lai, Yeh, Ko, & Chiang, 2012; Lei, Wang, Chen, Ni, & Lei, 2013; Mishra, Agarwal, Sharma, & Bedi, 2014; Run, Horng, Lai, Kao, & Chen, 2012; Vahedi, Zoroofi, & Shiva, 2012; Y.-R. Wang, Lin, & Yang, 2011) use the weighted sum approach for optimization, where the objectives of the fitness function are combined additively using weighting factors. One limitation of this approach is that the optimum solution depends on the values of the weighting factors, which are determined experimentally or heuristically.

Recently, Abdelhakim, Saleh, and Nassar (2015) proposed a fitness function to optimize the embedding strength parameters that were employed for embedding each watermark bit individually. In this fitness function, the robustness of a watermark bit was estimated through the achieved quality value. Hence, a single metric reflects both robustness and quality, and thus no weighting factors were needed.

Loukhaoukha (2013) employed a simple optimization algorithm, where its fitness function was evaluated using the exponential weighted criterion. This approach has the same limitations encountered in the weighted sum approach. J. Wang et al. (2011) applied the Non-dominated Sorting Genetic Algorithm II (NSGA II), which is an efficient multi-objective optimization technique. The fitness function ranked the solutions according to the non-dominated sorting method. Hence, the fitness of each solution was its assigned rank. Better performance, in terms of both quality and robustness, was achieved compared to the weighted sum approach. However, it is more complex.

The problem of optimizing one objective while constraining the others, by predefined thresholds, is known as the e-constrain problem (Marler & Arora, 2004). This multi-objective optimization technique is suitable for watermarking applications that define a limit on some of the watermarking objectives. Huang and Wu (2009) presented a fidelity-guaranteed robust watermarking method for achieving a pre-defined quality. The selected solutions, per optimization iteration, were pre-processed before applied to the fitness function. Then the fitness of each solution was evaluated through a weighted sum approach.

In general, multi-objective optimization algorithms applied within robust watermarking are uncommonly utilized due to their complexity. The weighted sum approach is considered to be a simple multi-objective optimization method according to Marler and Arora (2004). However, it is usually referred to as a single-objective optimization (J. Wang et al., 2011), when applied within watermarking. Moreover, it is difficult to find the optimum weighting factors. Note that due to the required computations, optimized watermarking approaches are suited to delay-tolerant applications. However, the advances in microprocessors would reduce the computational delay, enabling wider range of applications.

In this paper, we consider a challenging watermarking problem of achieving robustness without degrading the quality level beneath a predetermined threshold. Here, we consider a fixed payload. As mentioned earlier, mitigating attacks is essential for many watermarking applications, some of which might have quality of service requirements regarding the image quality, such as in Broadcast monitoring (Fujiyoshi & Kiya, 2004; Tachibana, Fujiyoshi, & Kiya, 2004a,2004b).

Note that the higher the application's tolerance to distortion, the more robustness to attacks the system can be. Therefore, it is important to design the watermarking system to achieve the highest robustness based on the application's maximum allowable distortion limit. To solve this problem, we define a new fitness function to be applied within an optimization algorithm that is designed to maximize the robustness while guaranteeing a predetermined quality. The e-constrained optimization problem is solved through the proposed approach, which is simple, effective, and does not require weighting factors.

The rest of the paper is organized as follows. In Section 2, the Artificial Bee Colony is described. In Section 3, the process of embedding and extracting the watermark is illustrated. The proposed work is presented in Section 4. Experimental results are demonstrated in Section 5. Finally, the paper is concluded in Section 6.

2. Artificial Bee Colony (ABC)

The Artificial Bee Colony (ABC), introduced in Karaboga (2005), is a simple population-based optimization algorithm, where a solution population is updated in each iteration. It has been applied in many practical optimization problems (Akay, 2013; Draa & Bouaziz, 2014; Hanbay & Talu, 2014; Li, Li, & Gong, 2014). The ABC algorithm simulates the foraging behavior of the bee swarm, such that each food source represents a possible solution for the optimization problem, and the quality of the source indicates the fitness of the associated solution. The foraging process involves three groups of bees:

(1) Employed bees: They are responsible for collecting food from food sources, and carrying information about them.
(2) Onlookers: They search for food sources to exploit according to the information received from the employed bees.
(3) Scouts: They search randomly, the environment surrounding the hive, for new food sources.

The ABC algorithm converges toward the optimal or near-optimal solution through the operation of the three groups of bees. The main steps of the algorithm are explained as follows:

1. Initialization:

Generate randomly the initial solution population of size NS, where each solution X_i has a dimension of D i.e. $X_i = (x_{i,1}, x_{i,2}, \ldots, x_{i,D})$ and $i = 1, 2, .., NS$. All Solutions are bounded between X_{min} and X_{max}, where $X_{min} = (x_{min,1}, x_{min,2}, \ldots, x_{min,D})$ and $X_{max} = (x_{max,1}, x_{max,2}, \ldots, x_{max,D})$. Solution $x_{i,j}$ is generated using the following equation:

$$x_{i,j} = x_{min,j} + rand(0,1) \cdot \left(x_{max,j} - x_{min,j}\right), \quad (1)$$

where $j = 1, 2, .., D$, and rand(0,1) is a random number between zero and one. After generating all NS solutions, their fitness values are calculated.

2. Employed bees phase:

Each employed bee updates its position (solution) to produce a new one.. The old solution is updated according to the following expression:

$$y_{i,j} = x_{i,j} + \phi_{i,j} \cdot \left(x_{i,j} - x_{k,j} \right), \tag{2}$$

where $j \in \{1, 2, \ldots, D\}$ and $k \in \{1, 2, \ldots, NS\}$ are randomly selected indexes, under the condition that the value of k must be different than that of i. The value $\Phi_{i,j}$ is a random number between −1 and 1, i.e. $\Phi_{i,j} \in [-1,1]$, and it controls the production of new solutions in the neighborhood of $x_{i,j}$. Then, the fitness value is calculated for the new solution and is compared with that of the old one. If the new solution has a higher fitness value, then it replaces the old one

3. Onlookers phase:

Each bee, in this phase, selects a food source to update using the same expression as in (2). The selection is based on a probability that depends on the fitness value associated to the food source.

4. Scouts phase:

The ABC algorithm assigns to each food source a value, referred to as "trials", which is initially set to zero. It represents the number of times that the update, of that source, fails to produce a better one. If a new source replaces an old one, its trials value will be reinitialized. The food source will be abandoned, if its trials exceed a predetermined value, called "limit" . Then, its assigned employed bee becomes a scout bee and starts to search randomly for a new source using the formula in (1).

5. Termination:

The ABC algorithm repeats steps 2, 3, and 4 until the number of iterations reaches a predefined value, referred to as MCN (Maximum Cycle Number), or a stopping criterion is met.

3. Watermark embedding and extraction

In this section, we describe the watermarking method that we presented in Abdelhakim et al. (2015). It is a Discrete Cosine Transform (DCT)-based technique, where a single watermark bit is embedded through modifying two adjacent 8 × 8 DCT blocks. The modification is performed by adjusting one coefficient in each block. According to the watermark bit, the values of the two selected coefficients are adjusted such that the difference between them is either greater or less than zero. The employed embedding technique is described in the following steps:

1. Divide the host image I, of size $N \times M$, into 8 × 8 blocks.
2. Transform each image block $I_{m,n}$ and its adjacent block $\mathrm{I}_{m+1,n}$ into DCT coefficients as follows:

$$I^{DCT}_{m,n} = DCT\ (I_{m,n}),\ \text{ and } I^{DCT}_{m+1,n} = DCT\ (I_{m+1,n}) \tag{3}$$

where m and n are the row and column indices of an image block.

3. Select the coefficient's position (i,j), for embedding a watermark bit, according to the following relation:

$$(i, j) = \begin{cases} \underset{(i,j)\in G_{even}}{\operatorname{argmin}} \left| I^{DCT}_{m,n}(i, j) - I^{DCT}_{m+1,n}(i, j) \right|, & if\ m\ is\ even, \\ \underset{(i,j)\in G_{odd}}{\operatorname{argmin}} \left| I^{DCT}_{m,n}(i, j) - I^{DCT}_{m+1,n}(i, j) \right|, & if\ m\ is\ odd, \end{cases} \tag{4}$$

where G_{even} and G_{odd}, are groups of predetermined locations, from which the coefficient's position is chosen. A location is selected from $\mathrm{G}_{\mathrm{even}}$ or $\mathrm{G}_{\mathrm{odd}}$ according to the row's position of the block $I_{m,n}$. It is then stored as a key data for watermark extraction.

4. Adjust the values of the two coefficients according to the watermark bit $w_{m,n}$, which is the bit located at the m^{th} row and the n^{th} column of the watermark image W. The adjustment is applied as follows:

$$\begin{bmatrix} I^{DCT}_{m,n}(i, j) \\ I^{DCT}_{m+1,n}(i, j) \end{bmatrix} = \begin{cases} \begin{bmatrix} I^{DCT}_{m+1,n}(i, j) \\ I^{DCT}_{m,n}(i, j) \end{bmatrix}, & if\,(W_{m,n} = 1\ and\ (I^{DCT}_{m,n}(i, j) \\ & -I^{DCT}_{m+1,n}(i, j)) < 0) or \\ & (W_{m,n} = 0\ and\,(I^{DCT}_{m,n}(i, j) \\ & -I^{DCT}_{m+1,n}(i, j)) > 0), \\ \begin{bmatrix} I^{DCT}_{m,n}(i, j) \\ I^{DCT}_{m+1,n}(i, j) \end{bmatrix}, & Otherwise. \end{cases} \tag{5}$$

5. Employ the embedding strength parameters, denoted by k and p, for robustness purpose. The first embedding strength (k) ensures that the absolute difference between the two modified coefficients is large enough to provide the required robustness. The second parameter (p) determines how much portion of the value k can be used in a coefficient adjustment. The addition of the strength parameters is illustrated as follows:

$$\begin{bmatrix} I^{DCT}_{m,n}(i, j) \\ I^{DCT}_{m+1,n}(i, j) \end{bmatrix} = \begin{cases} \begin{bmatrix} I^{DCT}_{m,n}(i, j) + p \cdot k \\ I^{DCT}_{m+1,n}(i, j) - (1 - p) \cdot k \end{bmatrix}, \\ \quad if\ W_{m,n} = 1\ and\ \left| I^{DCT}_{m,n}(i, j) - I^{DCT}_{m+1,n}(i, j) \right| < k, \\ \begin{bmatrix} I^{DCT}_{m,n}(i, j) - p \cdot k \\ I^{DCT}_{m+1,n}(i, j) + (1 - p) \cdot k \end{bmatrix}, \\ \quad if\ W_{m,n} = 1\ and\ \left| I^{DCT}_{m,n}(i, j) - I^{DCT}_{m+1,n}(i, j) \right| < k, \\ \qquad \begin{bmatrix} I^{DCT}_{m,n}(i, j) \\ I^{DCT}_{m+1,n}(i, j) \end{bmatrix}, \ Otherwise, \end{cases} \tag{6}$$

6. Apply the Inverse DCT (IDCT) to obtain the watermarked image blocks in the spatial domain. This is performed as follows:

$$I^{W}_{m,n} = IDCT\ \left(I^{DCT}_{m,n}\right),\ I^{W}_{m+1,n} = IDCT\ \left(I^{DCT}_{m,n}\right), \tag{7}$$

where $I^{W}_{m,n}$ is the block at the mth row and the nth column of the watermarked image I^{W}.

To extract the watermark, the DCT transform is applied to each 8 × 8 block of the watermarked image. Then, the coefficient's location is obtained using the key that is created at the embedding phase. The watermark bit $w_{m,n}$ is extracted according to the following relation:

$$w_{m,n} = \begin{cases} 1, & if\ \left(I^{WDCT}_{m,n}(i, j) - I^{WDCT}_{m+1,n}(i, j) \right) \geq 0, \\ 0, & Otherwise, \end{cases} \tag{8}$$

where I^{WDCT} is the watermarked image in the DCT domain.

4. Proposed fitness function

This section describes the proposed fitness function, through which the watermarking optimization is guided toward the maximum robustness under a predefined quality. The optimization problem is to search for the optimum embedding strength parameters (k and p) for embedding the watermark. The problem can be formulated as follows:\

$$\begin{aligned} &\text{Maximize } R\left([kp]\right) \\ &\text{Subject to : } Q\left([kp]\right) \geq Q_{th}, \end{aligned} \tag{9}$$

where $R(.)$ and $Q(.)$ are the robustness and the quality achieved using the solution $[k\ p]$, respectively, and Q_{th} is the predefined quality threshold value.

The proposed fitness function, illustrated in Fig. 1, ranks the solutions according to their impact on the defined optimization problem. This is performed through two main processes. The first process is the allocation procedure, applied to each solution individually. In this step, solutions are divided into two groups, where each

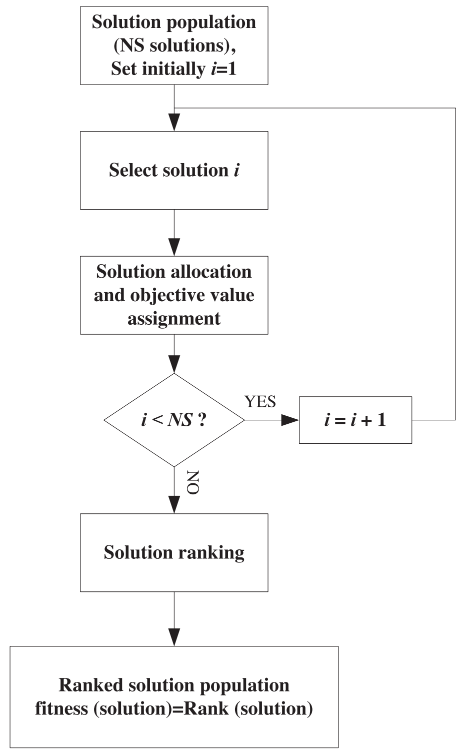


Fig. 1. Proposed fitness function.

group is responsible for a different objective (one is for quality and the other is for robustness). In the second step, all the allocated solutions are recombined and ranked in one population. This is explained in more details from the following flowchart.

The proposed solution allocation is illustrated in Fig. 2. A solution is allocated to one of two groups according to its achieved quality and the predetermined quality threshold that reflects the distortion limit. For a given solution $[k\ p]$, the achieved quality Q is evaluated. If the achieved quality is less than the quality threshold Q_{th}, the corresponding solution is assigned to a group, referred to as “Quality group”. Otherwise, the robustness objective R_t is evaluated, and the solution is assigned to another group, referred to as “Robustness group”.

The robustness R_t is calculated as follows:

$$R_t = \sum_{i=1}^{N_a} R_i \ , \tag{10}$$

where R_i is the robustness measured against the ith attack, and N_a is the total number of attacks.

In the Quality group, the solution’s objective value is its achieved quality Q. Note that, the solutions of this population do not satisfy the quality condition. Therefore, the optimization process will focus on finding solutions with higher quality regardless of their achieved robustness, until the quality satisfies the defined constraint. On the other hand, a solution in the Robustness group is assigned an objective value equal to its achieved robustness R_t. This is because the achieved quality constraint is satisfied. Thus, the robustness is the main objective in this group. Hence, each group is now considered a solution population for a single-objective optimization problem. That is, the multi-objective problem is converted into two single-objective optimization problems.

The proposed allocation is applied to each solution until they are all distributed between the Quality and the Robustness groups. After that, the two groups are recombined in order to complete the optimization process, since the optimization process operates only over one solution population per iteration, and a fitness value must be assigned to each solution. In the following steps, the proposed recombining and ranking process is described:

Step 1: Sort the solutions of the Robustness and the Quality groups according to their assigned objective values, such that:

$$\text{Sorted Robustness population} = \begin{bmatrix} [k\ p]_1 \\ [k\ p]_2 \\ . \\ . \\ [k\ p]_{Nr} \end{bmatrix}_R , \tag{11}$$

$$\text{Sorted Quality population} = \begin{bmatrix} [k\ p]_1 \\ [k\ p]_2 \\ . \\ . \\ [k\ p]_{Nq} \end{bmatrix}_Q , \tag{12}$$

where $[.]_R$ and $[.]_Q$ are the set of solutions allocated to the Robustness and the Quality groups, respectively. Moreover, Nr and Nq are the total number of solutions in the Robustness and the Quality groups, respectively. The solutions, of each group, are sorted in descending order with respect to their objective values, such that:
Objective $([k\ p]_1)_R >$ Objective $([k\ p]_2)_R > \ . . . \ >$ Objective $([k\ p]_{Nr})_R$
Objective $([k\ p]_1)_Q >$ Objective $([k\ p]_2)_Q > \ . . . \ >$ Objective $([k\ p]_{Nq})_Q$
where Objective $([k\ p]_i)_R$ and Objective $([k\ p]_i)_Q$ are the robustness objective and the quality objective of the i^{th} solution in the Robustness and Quality group, respectively.

Step 2: Combine the two sorted groups to form one ranked population such that the ranks of its solutions represent their fitness values. The ranked population is obtained as follows:

$$\text{Ranked population} = \begin{bmatrix} \begin{bmatrix} [k\ p]_1 \\ [k\ p]_2 \\ . \\ . \\ [k\ p]_{Nr} \end{bmatrix}_R \\ \begin{bmatrix} [k\ p]_1 \\ [k\ p]_2 \\ . \\ . \\ [k\ p]_{Nq} \end{bmatrix}_Q \end{bmatrix}, \tag{13}$$

The recombined population is ranked such that, the rank of a solution $[k\ p]_i$ is higher than that of solution $[k\ p]_j$ if one of the following cases is satisfied:

Case 1: $[k\ p]_i \in [.]_R$, and $[k\ p]_j \in [.]_Q$
In this case, solution $[k\ p]_i$ satisfies the quality condition, while solution $[k\ p]_j$ does not. Hence, solution $[k\ p]_i$ is better than solution$[k\ p]_j$ in terms of the defined optimization objective, and hence it has a higher rank.
Case 2: Objective $([k\ p]_i)_R >$ Objective $([k\ p]_j)_R$
In this case, both solutions belong to the Robustness group. Hence, the solution with the larger robustness is assigned a higher rank.
Case 3: Objective $([k\ p]_i)_Q >$ Objective $([k\ p]_j)_Q$
In this case, both solutions are in the Quality group. Therefore, they do not satisfy the quality condition. However, solution $[k\ p]_i$ has a higher rank because it achieved higher quality. Thus, solution $[k\ p]_i$ is selected.

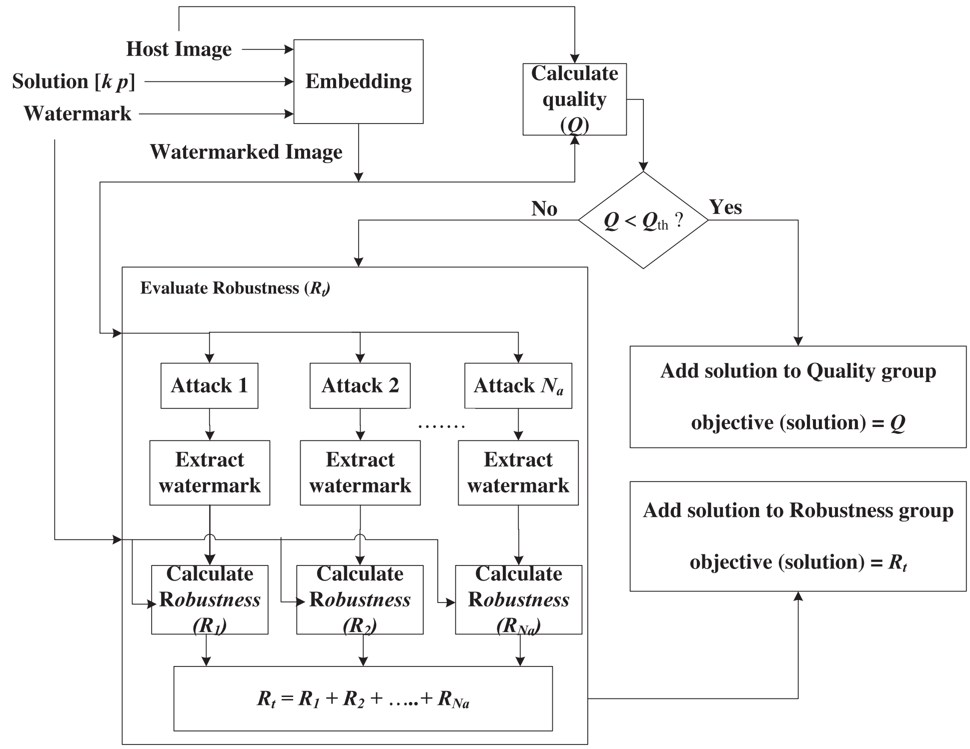


Fig. 2. Solution allocation and objective value calculation.

Table 1
ABC optimization parameters.

ABC Parameter		Value
Number of food sources (NS)		30
Maximum cycle number (MCN)		10
Limit		6
Solution space [k p]	Lower bound:	[0 0]
	Upper bound:	[80 1]
Onlooker selection probability:		Prob.(sol.) = 1/2(rank(sol.))
Fitness Function parameters	Attack 1:	JPEG 20% QF
	Attack 2:	Median filter of window size 3×3

As shown from Fig. 2, the proposed fitness function measures only the robustness objective when the quality objective exceeds the threshold value. Hence, saving the time consumed from applying attacks to the watermarked image. The defined fitness function is used with the ABC algorithm, described in Section 2, to find the optimum embedding parameters for robust image watermarking. The performance of the proposed approach will be presented in the following section.

5. Experimental results

In this section, the performance of the proposed scheme is evaluated through simulation experiments. Sixteen standard grayscale pictures of size 512×512 are selected as host images for a fixed watermark logo image of size 32×32 bits. In Fig. 3, the host images and the watermark logo are shown. The proposed technique inserts a watermark of size 63×64 bits inside a 512×512 host. Thus, the logo is duplicated three times for redundancy.

The optimization parameters of the ABC algorithm are listed in Table 1. We considered two different attacks for robustness evaluation, i.e. $N_a = 2$. The first attack is the JPEG compression with quality factor of 20%, while the second attack is a median filter of kernel size 3×3. The optimization objective is to maximize the robustness against the two attacks, while maintaining the quality level above a predefined limit. The proposed approach has been tested under different quality thresholds, as will be illustrated in the following.

5.1. Quality measurement

The quality of the watermarked image can be measured using many metrics. These metrics are based on either mathematical models or human visual system (HVS) models (Bedi, Bansal, & Sehgal, 2012; Farhan & Bilal, 2011; Kumsawat, Pasitwilitham, Attakitmongcol, & Srikaew, 2011; Rohani & Avanaki, 2009). In this work, one metric from each model is selected. The first metric is the Peak Signal to Noise Ratio (PSNR), which is commonly used to evaluate the quality performance of watermarking systems. The PSNR is evaluated by comparing the host image I, of size $N \times M$, with the watermarked image I_W as follows:

$$\mathrm{PSNR} = 10 \log \frac{255^2}{\frac{1}{N\times M}\sum_{i=1}^{N}\sum_{j=1}^{M}\left(I(i,j) - I_W(i,j)\right)^2}, \tag{14}$$

The quality indicator can be based on the human visual system, which represents the quality with respect to the human eye. Therefore, it could be more suitable for defining the distortion limit. Hence, it is used here for setting the quality threshold. A possible visual-based quality metric is reflected in the PSNR-JND (Peak

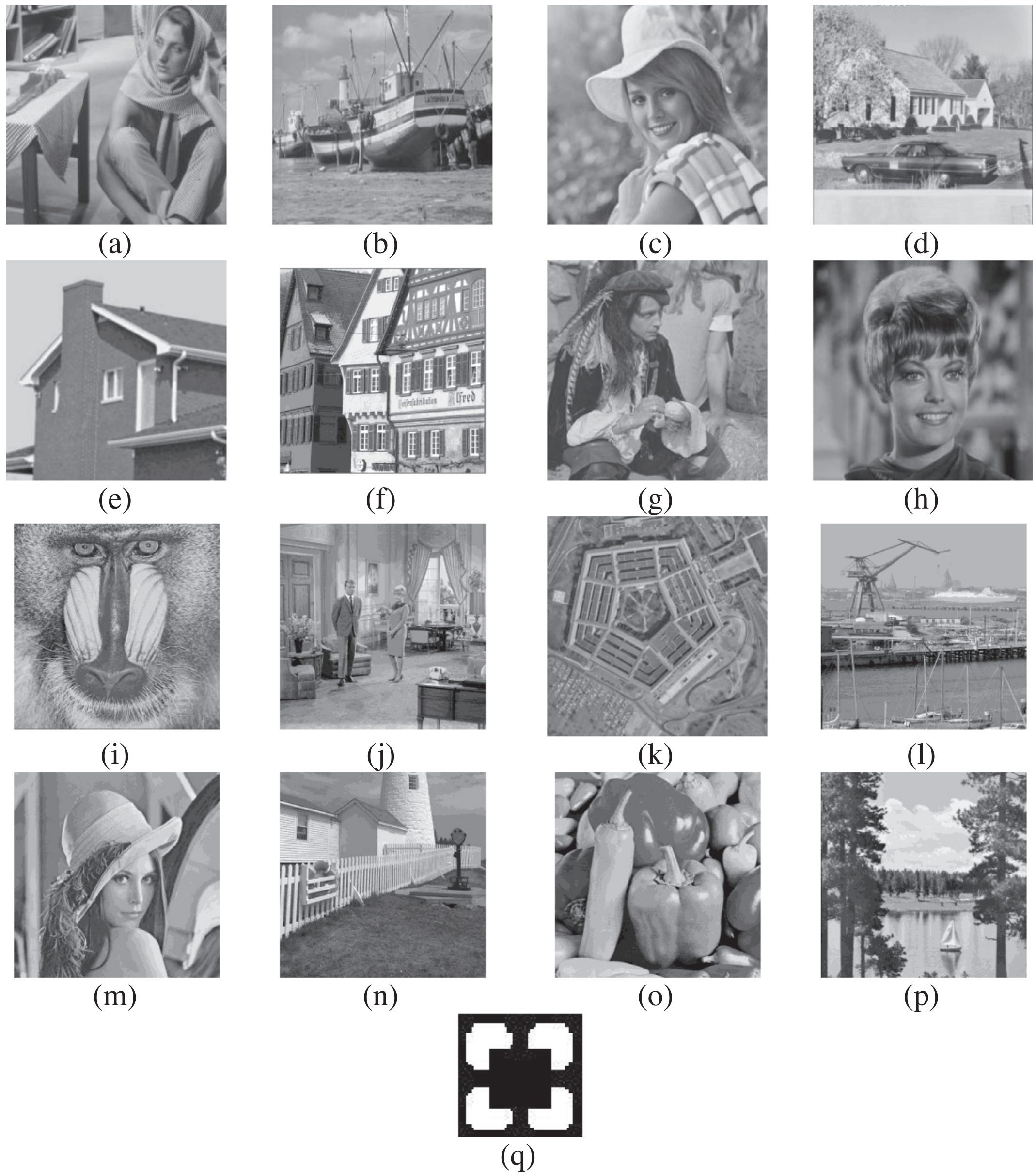


Fig. 3. The host images and the watermark logo: (a) Barbara, (b) Boat, (c) Elaine, (d) House1, (e) House2, (f) Houses3, (g) Pirate, (h) Zelda, (i) Baboon, (j) Living room, (k) Pentagon, (l) Kiel, (m) Lena, (n) Lighthouse, (o) Peppers, (p) Lake, (i) Watermark logo.

Signal to Noise Ratio-Just Noticeable Difference), which is based on the DCT coefficients values (Dimauro, 2012). The calculation of this metric involves a database of test images, where the quality of each image was evaluated subjectively. Hence, it offers reliable measurement compared to other traditional HVS-based quality metrics (Wang & Bovik, 2002; Wang, Bovik, Sheikh, & Simoncelli, 2004).

The PSNR-JND is calculated using the same expression used for the PSNR, but it computes the MSE (Mean Square Error) between the host and the watermarked images in the DCT domain. The perceptual error between the two images is calculated by dividing the DCT error by the minimum DCT coefficients that are able to produce a visible image. The minimum DCT coefficients are referred to as JND (Just Noticeable Difference), and are calculated experimentally. The PSNR-JND is calculated as follows:

$$\text{PSNR - JND} = 10\log\frac{255^2}{MSE_{JND}}, \tag{15}$$

where

$$MSE_{JND} = \frac{1}{N\times M}\sum_{l=1}^{N_l}\sum_{i=1}^{8}\sum_{j=1}^{8}\left[d_{ij}^{(l)}\right]^2, \tag{16}$$

l is the index of the 8×8 block, and N_l is the total number of blocks. Moreover, i and j are the indices for the row and column of the DCT coefficient's location in the lth block, respectively. The difference $d_{ij}{}^{(l)}$ is calculated for the lth block using the following expression:

$$d_{ij}^{(l)} = \frac{C_{ij}^{(l)} - Cw_{ij}^{(l)}}{t_{ij}^{(l)}}, \tag{17}$$

where C and Cw are the DCT coefficients corresponding to the host and the watermarked images, respectively. The minimum DCT coefficients $t^{(l)}$ for the lth block is evaluated as follows:

$$t^{(l)} = t\left(C_{00}^{(l)}/C_{00}^{avg}\right)^a, \tag{18}$$

Table 2
The highest quality that can be achieved, for each host image, in terms of PSNR and PSNR-JND (dB).

Host image	Highest quality (Q_{max})	
	PSNR	PSNR-JND
Barbara	52.61	30.90
Boat	51.13	29.43
Elaine	55.23	33.33
House1	50.79	29.35
House2	57.89	35.58
House3	47.50	26.16
Pirate	52.19	30.19
Zelda	57.01	35.44
Baboon	48.09	26.49
Living room	52.43	30.95
Pentagon	49.20	27.60
Kiel	51.18	29.05
Lena	53.94	31.68
Lighthouse	52.24	31.47
Peppers	54.60	32.87
Lake	49.52	27.54
Average (dB)	52.22	30.50

Table 3
The established qualities, in terms of PSNR-JND (dB), for the watermarked images using the proposed scheme under different quality threshold Q_{th}.

Host image	$Q_{th}=15$	$Q_{th}=20$	$Q_{th}=25$
Barbara	16.87	20.11	25.07
Boat	16.47	20.00	25.08
Elaine	18.85	20.00	25.00
House1	17.85	20.15	25.14
House2	18.34	20.01	25.04
House3	15.01	20.12	25.12
Pirate	16.47	20.01	25.08
Zelda	18.68	20.20	25.03
Baboon	15.08	20.03	25.00
Living room	18.23	20.00	25.61
Pentagon	17.01	20.09	25.00
Kiel	15.34	20.02	25.11
Lena	17.89	20.16	25.03
Light house	17.01	20.18	25.14
Peppers	17.94	20.05	25.25
Lake	15.93	20.01	25.02

Where $C_{00}{}^{(l)}$ is the DC value of the lth block, and $C_{00}{}^{avg}$ is the average of the DC values over all blocks of the image. The value of a is set such that $0 < a < 1$. The 8×8 matrix t is calculated by the aid of experimental results, similar to that in Dimauro (2012).

The optimization process is carried out by setting a quality threshold Q_{th} value such that the watermark robustness is maximized under the constraint of maintaining the achieved quality level above Q_{th}. For any watermarking system, there is a maximum achievable quality (Q_{max}) that depends on the embedding method and the host image. Hence, for any Q_{th}, the optimized watermarked image quality cannot exceed Q_{max}.

Table 2 shows the highest achieved quality for each of the sixteen host images. According to the user defined bounds of the strength parameters, the results are obtained through embedding the watermark using their lower bounds, in order to cause the least possible distortion.

As mentioned above, the PSNR-JND is used for setting Q_{th}. Hence, it will be used also for measuring the quality objective of the proposed fitness function. We then measure the quality performance using the PSNR metric, which is commonly used for performance evaluation. According to Table 2, three values are chosen for the quality threshold Q_{th}, which are less than Q_{max} for all host images. These values are: 15, 20, and 25 dB

Table 3 shows the achieved PSNR-JND of the watermarked images using the proposed method for each of the sixteen host images. The results show that the achieved quality levels are higher than the predefined threshold in all cases. Therefore, the value of Q_{th} acts as a floor for the achieved quality. In other words, the solution that leads to the maximum robustness and satisfies the optimization constraint, will in turn results in a quality value greater than or equal to Q_{th}. As can be shown from the table, for the case of $Q_{th} = 20$ and 25 dB, the overall quality is very close to Q_{th}. For $Q_{th} = 15$ dB, which is relatively low, there could be more than one solution that achieves the maximum robustness (BCR = 100%). In the proposed approach, the solution with the highest quality is selected.

The effectiveness of the proposed approach is demonstrated through performance comparisons with conventional methods for watermarking optimization. Existing methods are mostly carried out using weighted sum fitness function (WS_FF), which can be formulated as follows:

$$WS\_FF = Q + \sum_{i=1}^{N_a} \lambda_i \cdot R_i, \tag{19}$$

where λ_i is the weighting factor for the robustness objective R_i against the i^{th} attack, and Q is the quality objective. The values of these factors are determined either experimentally or heuristically. In our experiments, Q is measured in terms of PSNR, and

Table 4
Quality comparison in terms of PSNR (dB).

Host image	(Das, et al., 2014)	(J. Wang, et al., 2011)	Optimized watermarking using			
			WS_FF $\lambda_1 = \lambda_2 = 20$	Proposed fitness function		
				$Q_{th}=15$	$Q_{th}=20$	$Q_{th}=25$
Barbara	41.06	38.73	41.95	38.69	41.88	46.89
Boat	40.46	38.82	41.90	38.13	41.61	46.68
Elaine	41.76	40.00	42.70	40.41	41.57	46.55
House1	39.99	38.55	42.19	39.08	41.33	46.38
House2	42.58	40.01	43.69	40.01	41.71	46.73
House3	38.45	37.67	40.47	36.51	41.55	46.37
Pirate	40.85	38.84	43.10	38.34	41.87	46.91
Zelda	42.92	39.57	42.40	40.54	41.94	46.80
Baboon	39.50	37.87	41.23	36.69	41.62	46.61
Living room	41.03	38.80	42.71	39.64	41.30	46.91
Pentagon	39.15	38.44	43.06	38.46	41.65	46.64
Kiel	40.17	38.43	42.12	36.73	41.21	46.64
Lena	41.84	39.22	41.96	39.74	41.95	46.89
Light house	40.77	38.27	42.25	38.23	41.32	46.23
Peppers	41.74	39.07	42.16	39.90	41.85	47.07
Lake	40.11	38.84	41.48	37.71	41.79	46.87

the values of the weighting factors are set to 20 (for $N_a = 2$) in order to balance the weights of the different objectives of the fitness function. Since Q and R_i are approximately equal to 40 dB and 1, respectively.

In Table 4, a comparison is provided between our proposed approach and existing embedding methods in Das, Panigrahi, Sharma, and Mahapatra, (2014) and J. Wang et al. (2011) in terms of the achieved quality. The performance of the proposed watermarking method is optimized by the ABC algorithm using the proposed fitness function and the WS_FF in (19). The results show that, as expected, the achieved quality increases by using larger Q_{th}. Thus, the quality of the watermarked images can be controlled through adjusting Q_{th}. In addition, it can be noticed that the quality of the proposed method outperforms that of the other techniques, for $Q_{th} > 20$ dB

5.2. Robustness measurement

The robustness of the watermark is examined by evaluating the performance of the watermarking system under attacks, and measuring the similarity between the embedded and the extracted watermark. In our experiments, the bit correct rate (BCR) is used to measure the similarity. It is calculated as follows:

$$BCR = \frac{\sum_{n=1}^{N_W} \sum_{m=1}^{M_W} \overline{(W(n,m) \oplus W'(n,m))}}{N_W \times M_W}, \tag{20}$$

where W and W' are the embedded and the extracted watermark of size $N_W \times M_W$, respectively. The operators $\oplus$ and $\overline{(.)}$ are the XOR and the NOT operators, respectively.

Various attacks are considered for evaluating the robustness performance. They were applied using Stirmark and Matlab image processing toolbox.

Attacks applied using Stirmark are:

- JPEG compression
- Median filter
- Additive White Gaussian Noise (AWGN)
- Scaling
- Rotation

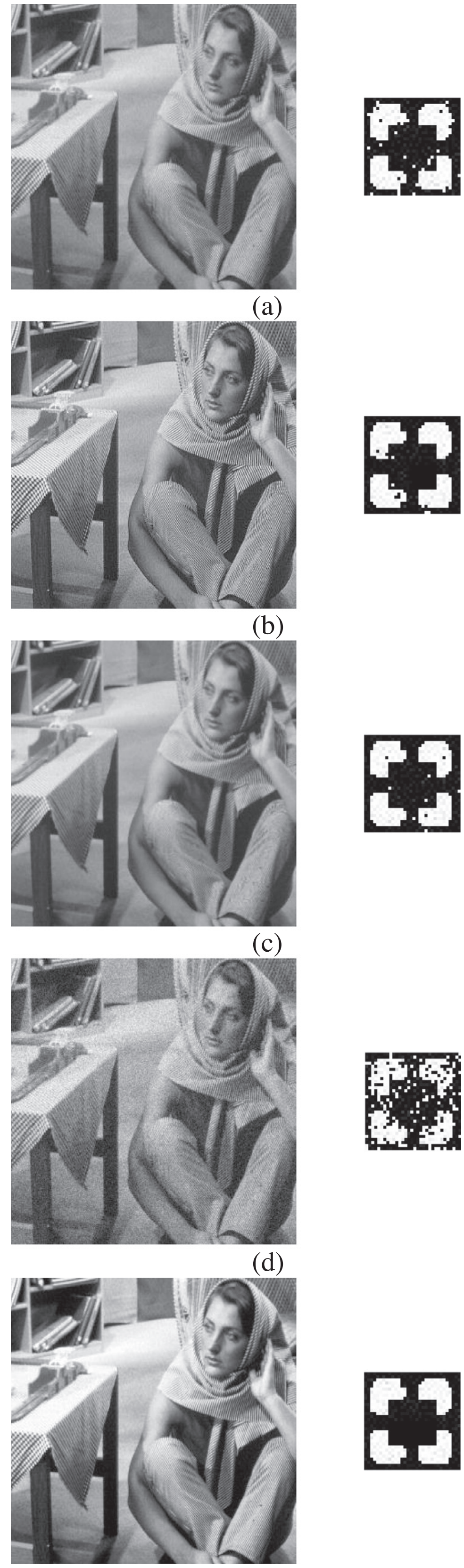
Attacks applied using Matlab are:

- Low pass filtering
- Average filtering
- Salt and pepper noise
- Sharpening
- Histogram Equalization
- Gamma correction
- Cropping

The severity of any attack is represented by its degree. A range of degrees is considered for robustness analysis.

We apply our proposed watermarking approach with $Q_{th} = 20$ dB to illustrate the effect of the attacks on the watermarked image and the extracted watermark. Fig. 4 shows the watermarked image and the extracted watermark, under different attacks.

The robustness performance is illustrated through the comparison as shown in Table 5, where the results are obtained by calculating the average BCR, over the sixteen host images. It can be seen that the robustness of the proposed method is superior to that of other methods. However, the robustness against the JPEG attack, for the case when $Q_{th} = 25$, is slightly lower than that of (Das et al., 2014). The robustness of the proposed fitness function depends on the predefined value Q_{th}, such that, the robustness decreases as Q_{th} increases. It is also observed that, compared to the WS_FF, the robustness corresponding to the proposed fitness function is



(a)
(b)
(c)
(d)
(e)

Fig. 4. The watermarked image and the extracted watermark, after applying different attacks: (a) JPEG compression with QF = 20%, (b) Sharpening, (c) Median filter with window size 3 × 3, (d) AWGN with var. = 0.005, (e) Histogram equalization.

Table 5
Robustness comparison in terms of the average BCR over the sixteen host images.

Attack type	Attack degree		(Das, et al., 2014)	(J. Wang, et al., 2011)	Optimized watermarking using			
					WS_FF	Proposed fitness function		
					$\lambda_1 = \lambda_2 = 20$	$Q_{th} = 15$	$Q_{th} = 20$	$Q_{th} = 25$
JPEG	QF	15%	0.677	0.620	0.761	0.960	0.821	0.555
		20%	0.787	0.670	0.947	0.999	0.969	0.637
		25%	0.887	0.697	0.988	1	0.994	0.725
		30%	0.951	0.719	0.996	0.999	0.998	0.819
		35%	0.974	0.747	0.998	1	0.999	0.887
		40%	0.997	0.772	0.999	1	0.999	0.925
		50%	0.999	0.815	1	1	1	0.970
		60%	0.999	0.851	1	1	0.999	0.983
		70%	0.999	0.892	1	1	0.999	0.993
		80%	0.999	0.936	0.999	1	1	0.998
		90%	0.999	0.973	1	1	1	0.999
Gaussian LPF	Window size:	3×3	0.995	0.997	0.999	1	1	0.999
		4×4	0.896	0.817	0.966	0.999	0.994	0.958
		5×5	0.996	0.711	0.964	0.998	0.992	0.948
Sharpening	Window size:	3×3	0.944	0.984	0.994	0.999	0.995	0.967
		3×3	0.921	0.664	0.987	0.998	0.990	0.940
Average filter	Widow size:	5×5	0.762	0.550	0.864	0.931	0.878	0.791
		7×7	0.592	0.514	0.615	0.645	0.617	0.584
		9×9	0.511	0.502	0.468	0.447	0.464	0.476
		3×3	0.915	0.698	0.979	0.997	0.981	0.917
Median filter:	Window size:	5×5	0.781	0.588	0.877	0.939	0.887	0.796
		7×7	0.633	0.532	0.659	0.711	0.669	0.626
		9×9	0.543	0.520	0.519	0.515	0.518	0.527
AWGN	Noise level:	20%	0.494	0.574	0.568	0.631	0.571	0.544
		30%	0.494	0.537	0.548	0.577	0.545	0.531
		40%	0.496	0.530	0.534	0.563	0.541	0.513
Salt & pepper	Density:	0.01	0.914	0.927	0.964	0.995	0.973	0.899
		0.05	0.653	0.792	0.796	0.918	0.817	0.681
		0.1	0.550	0.709	0.700	0.833	0.719	0.618
Histogram equalization			0.902	0.981	0.994	0.999	0.996	0.984
Gamma correction	Gamma value:	0.9	0.946	0.998	0.998	0.999	0.999	0.989
		0.2	0.999	0.998	1	1	1	1
Rescaling	Rescale ratio:	50%	0.991	0.820	0.999	0.999	0.999	0.989
		75%	0.990	0.940	0.999	1	0.999	0.991
		150%	0.935	0.857	0.978	0.995	0.980	0.928
Cropping	Upper left quad.	0.983	0.687	0.996	0.998	0.996	0.995	
	Upper right quad.	0.988	0.675	0.994	0.997	0.994	0.993	
	Lower left quad.	0.992	0.996	0.989	0.990	0.988	0.986	
	Lower right quad.	0.978	0.995	0.988	0.990	0.987	0.984	
Rotation	Degree:	−0.75	0.507	0.495	0.489	0.477	0.489	0.490
		−0.5	0.580	0.507	0.605	0.627	0.606	0.583
		−0.25	0.811	0.624	0.885	0.935	0.895	0.822
		0.25	0.815	0.618	0.883	0.936	0.891	0.820
		0.5	0.585	0.510	0.595	0.620	0.603	0.580
		0.75	0.514	0.500	0.487	0.484	0.483	0.493

higher for the case when $Q_{th} = 15$ and 20 dB, although, there is a slight decrease in BCR when $Q_{th} = 25$ dB

The results shown in Tables 4 and 5 verify that the proposed method provides better compromise between quality and robustness than that of the compared methods. Furthermore, the required quality can be controlled by adjusting Q_{th}. However, higher quality could come at the expense of some degradation in robustness due to the conflict between them.

6. Conclusion

In this paper, we solved a challenging design problem in watermarking systems applied to multimedia applications with a guaranteed quality requirement. A simple and effective method was proposed to achieve high robustness under a constraint on the maximum distortion level by introducing a novel fitness function to be applied within a meta-heuristic process. The embedding strength parameters were optimized to provide the maximum robustness under a predefined constraint on the quality level. In the proposed fitness function, the robustness and quality objectives are optimized separately by decoupling the problem into two single-objective optimization sub-problems. Hence, there is no need for weighting factors that are typically required in conventional watermarking optimization schemes. A recent embedding method was employed, and then optimized using the ABC algorithm with the proposed fitness function. The effectiveness of the proposed fitness function was illustrated through performance comparisons with traditionally used fitness functions based on the weighted sum approach. Recent watermarking techniques were considered for comparison. The results showed the impact of the watermarking design on both robustness and quality. It is practical to design the watermarking system, to achieve the highest possible robustness, based on the application's maximum allowable distortion limit. The proposed approach provides the means of controlling the quality level by adjusting a predefined threshold. It was observed that the watermarking quality has a maximum value, which depends on the host image, embedding technique, and the bounds of the solution space.

It can be concluded form the experimental results, which are carried out under various attacks and quality thresholds, that the proposed approach achieves enhanced robustness for image watermarking and satisfies the imposed quality constraint.

References

Abdelhakim, A. M., Saleh, H. I., & Nassar, A. M. (2015). Quality metric-based fitness function for robust watermarking optimisation with Bees algorithm. *IET image processing*.

Akay, B. (2013). A study on particle swarm optimization and artificial bee colony algorithms for multilevel thresholding. *Applied Soft Computing, 13*, 3066–3091.

Ali, M., Ahn, C. W., & Siarry, P. (2014). Differential evolution algorithm for the selection of optimal scaling factors in image watermarking. *Engineering Applications of Artificial Intelligence, 31*, 15–26.

Aslantas, V. (2009). An optimal robust digital image watermarking based on SVD using differential evolution algorithm. *Optics Communications, 282*, 769–777.

Bedi, P., Bansal, R., & Sehgal, P. (2012). Multimodal biometric authentication using PSO based watermarking. *Procedia Technology, 4*, 612–618.

Cox, I. J., Miller, M. L., Bloom, J. A., & Honsinger, C. (2002). *Digital watermarking*: 53. Springer.

Das, C., Panigrahi, S., Sharma, V. K., & Mahapatra, K. (2014). A novel blind robust image watermarking in DCT domain using inter-block coefficient correlation. *AEU-International Journal of Electronics and Communications, 68*, 244–253.

Dimauro, G. (2012). A new image quality metric based on human visual system. In *Virtual environments human-computer interfaces and measurement systems (VECIMS), 2012 IEEE international conference on* (pp. 69–73). IEEE.

Draa, A., & Bouaziz, A. (2014). An artificial bee colony algorithm for image contrast enhancement. *Swarm and Evolutionary Computation, 16*, 69–84.

Farhan, A. A., & Bilal, S. (2011). A novel fast and robust digital image watermarking using Bee Algorithm. In *Multitopic conference (INMIC), 2011 IEEE 14th international* (pp. 82–86). IEEE.

Fujiyoshi, M., & Kiya, H. (2004). An image-quality guananteed method for quantization-based watermarking using a DWT. *International conference on image processing*.

Fung, C., Gortan, A., & Godoy, W., Jr (2011). A review study on image digital watermarking. In *The tenth international conference on networks-ICN* (pp. 24–28).

Hammouri, A. I., Alrifai, B., & Al-Hiary, H. (2013). An intelligent watermarking approach based particle swarm optimization in discrete wavelet domain. International Journal of Computer Science Issues IJCSI, *10*, 330–338.

Hanbay, K., & Talu, M. F. (2014). Segmentation of SAR images using improved artificial bee colony algorithm and neutrosophic set. *Applied Soft Computing, 21*, 433–443.

Huang, C.-H., & Wu, J.-L. (2009). Fidelity-guaranteed robustness enhancement of blind-detection watermarking schemes. *Information Sciences, 179*, 791–808.

Husain, F. (2012). A survey of digital watermarking techniques for multimedia data. *Int'l Journal of Electronics and Communication Engineering, 2*, 37–43.

Karaboga, D. (2005). *An idea based on honey bee swarm for numerical optimization*. Erciyes university, engineering faculty, computer engineering department Technical report-tr06.

Kumsawat, P., Pasitwilitham, K., Attakitmongcol, K., & Srikaew, A. (2011). An artificial intelligent technique for robust digital watermarking in multiwavelet domain. *World Academy of Science, Engineering and Technology, 60*.

Lai, C.-C., Yeh, C.-H., Ko, C.-H., & Chiang, C.-Y. (2012). Image watermarking scheme using Genetic algorithm. In *Genetic and evolutionary computing (ICGEC), 2012 sixth international conference on* (pp. 476–479). IEEE.

Lei, B., Wang, T., Chen, S., Ni, D., & Lei, H. (2013). Robust watermarking scheme for medical image using optimization method. In *Information, communications and signal processing (ICICS) 2013 9th international conference on* (pp. 1–4). IEEE.

Li, B., Li, Y., & Gong, L. (2014). Protein secondary structure optimization using an improved artificial bee colony algorithm based on AB off-lattice model. *Engineering Applications of Artificial Intelligence, 27*, 70–79.

Liu, J., & He, X. (2005). A review study on digital watermarking. In *Information and communication technologies, 2005. ICICT 2005. first international conference on* (pp. 337–341). IEEE.

Loukhaoukha, K. (2013). Image watermarking algorithm based on multiobjective ant colony optimization and singular value decomposition in wavelet domain. *Journal of Optimization, 2013*.

Marler, R. T., & Arora, J. S. (2004). Survey of multi-objective optimization methods for engineering. *Structural and multidisciplinary optimization, 26*, 369–395.

Mishra, A., Agarwal, C., Sharma, A., & Bedi, P. (2014). Optimized gray-scale image watermarking using DWT–SVD and firefly algorithm. *Expert Systems with applications, 41*, 7858–7867.

Olanrewaju, R. F., Khalifa, O. O., Hashim, A.-H., Zeki, A. M., & Aburas, A. A. (2011). Forgery detection in medical images using complex valued neural network (CVNN). *Australian Journal of Basic and Applied Sciences, 5*, 1251–1264.

Preda, R. O., & Vizireanu, D. N. (2010). A robust digital watermarking scheme for video copyright protection in the wavelet domain. *Measurement, 43*, 1720–1726.

Rohani, M., & Avanaki, A. N. (2009). A watermarking method based on optimizing SSIM index by using PSO in DCT domain. *2009 14th International CSI computer conference*.

Run, R.-S., Horng, S.-J., Lai, J.-L., Kao, T.-W., & Chen, R.-J. (2012). An improved SVD-based watermarking technique for copyright protection. *Expert Systems with Applications, 39*, 673–689.

Tachibana, T., Fujiyoshi, M., & Kiya, H. (2004). An image-quality guaranteed watermarking scheme with spreading spectrum of watermark. In *Communications and information technology, 2004. ISCIT 2004. IEEE international symposium on: 1* (pp. 330–334). IEEE.

Tachibana, T., Fujiyoshi, M., & Kiya, H. (2004). A watermarking scheme without reference images for broadcast monitoring. *Electronics and Communications in Japan (Part III: Fundamental Electronic Science), 87*, 22–32.

Vahedi, E., Zoroofi, R. A., & Shiva, M. (2012). Toward a new wavelet-based watermarking approach for color images using bio-inspired optimization principles. *Digital Signal Processing, 22*, 153–162.

Wang, J., Peng, H., & Shi, P. (2011). An optimal image watermarking approach based on a multi-objective genetic algorithm. *Information Sciences, 181*, 5501–5514.

Wang, Y.-R., Lin, W.-H., & Yang, L. (2011). An intelligent watermarking method based on particle swarm optimization. *Expert Systems with Applications, 38*, 8024–8029.

Wang, Z., & Bovik, A. C. (2002). A universal image quality index. *Signal Processing Letters, IEEE, 9*, 81–84.

Wang, Z., Bovik, A. C., Sheikh, H. R., & Simoncelli, E. P. (2004). Image quality assessment: From error visibility to structural similarity. *Image Processing, IEEE Transactions on, 13*, 600–612.

Yusof, Y., & Khalifa, O. O. (2007). Digital watermarking for digital images using wavelet transform. In *Telecommunications and Malaysia international conference on communications, 2007. ICT-MICC 2007. IEEE international conference on* (pp. 665–669). IEEE.

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