Applied Mathematics & Information Sciences
An International Journal

http://dx.doi.org/10.12785/amis/080632

A New Image Watermarking Scheme using Multi-Objective Bees Algorithm

Jiann-Shu Lee[1,*], *Jing-Wein Wang*[2] *and Kung-Yo Giang*[1]

[1] Department of Computer Science and Information Engineering, National University of Tainan, Taiwan
[2] Institute of Photonics and Communications, National Kaohsiung University of Applied Science, Kaohsiung, Taiwan

Received: 15 Nov. 2011, Revised: 15 Nov. 2013, Accepted: 1 Feb. 2014
Published online: 1 Nov. 2014

Abstract: The optimization of watermarked image fidelity and watermark robustness is an attractive research topic in image watermarking. In this paper, we propose a new image watermarking scheme based on multi-objective bees algorithm to promote watermarking robustness as well as fidelity. In contrast with the existing genetic algorithms (GAs) based approaches utilizing single objective optimization, we treat the image watermarking as a multi-objective optimization problem. Based on this new perspective, the inherent conflict existing in image fidelity and watermark robustness for image watermarking can be objectively handled. The experimental study shows that our method indeed outperform the conventional GA-based approaches in both robustness and fidelity. Furthermore, the proposed watermarking method can also provide solutions with higher stability.

Keywords: Watermarking, Multi-Objective Bees Algorithm, Genetic Algorithm

1 Introduction

Because of the rapid and extensive growth of the internet and popular digital recording and storage devices, digital content can be replicated, transmitted, and distributed in an effortless way. The protection of intellectual property rights for digital media has become an important issue. In recent years, digital watermarking, proposed to protect the copyright property of the legal owners and providers [1], has become an active research area. The techniques for watermarking still images can be classified into spatial-domain approaches and frequency-domain approaches. Spatial domain approaches tend to achieve fidelity while suffering from low robustness. On the contrary, the frequency-domain approaches show greater robustness because the watermark has been spread over the whole image, thus being resistant to cropping or cutting. The most recently proposed watermarking approaches [2–11] belong to the latter. One common problem confronted by these approaches is how to decide and choose the best embedding frequencies. For watermark embedding in the discrete cosine transform (DCT) domain, if we embed the watermark in the higher frequency bands, even though the watermarked image fidelity is good, it is vulnerable to the low pass filtering (LPF) attack. In contrast, if we embed the watermark in the coefficients in the lower frequency bands, it should be robust against common image processing attacks such as the LPF attack. However, the watermarked image fidelity greatly degrades. Hence, most recent researches choose to embed the watermarks into the middle-frequency bands to serve as a compromise between image fidelity and watermark robustness [12].

Even though the watermarks are embedded into the middle-frequency bands, the problem about how to choose the optimal embedding frequencies is still not solved [13]. Recently, artificial intelligence techniques have been applied to resolve this problem [14, 15]. Those methods [14, 15] treated the image watermarking problem as an optimization problem and then genetic algorithms were employed to solve that. Shieh and Huang et al. [14] proposed a DCT watermarking method based on the GA. The GA is applied to search for the locations to embed the watermark in the DCT coefficients so that the robustness and the watermarked image fidelity are simultaneously optimized. Wei et al. [15] presented an improved method to increase the speed of GA.

The image watermarking issue inherently possesses two conflicting goals, i.e. fidelity and robustness. The existing GA-based watermarking methods handle this by

* Corresponding author e-mail: cslee@mail.nutn.edu.tw

combining the two objectives into a single composite fitness function and then search for the optimal solution. Such approaches rely on the proper selection of the weights or utility functions to characterize the decision-maker's preferences. Hence, they face a predicament that they must consider the weights among objectives, and on the other hand, small perturbations in the weights can sometimes lead to quite different solutions. In practice, it can be very difficult to precisely and accurately select these weights, even for someone familiar with the problem domain. Besides, the existing GA based methods can not handle a practical requirement from users that gives them the corresponding optimally robust watermarked image when an acceptable fidelity such as peak-signal-to-noise ratio (PSNR) is specified.

To deal with the dilemma faced by the existing GA-based approaches, we propose a new scheme by treating the image watermarking as a multi-objective optimization problem rather than a single one like the existing GA-based approaches did. Hence, we have two objectives, i.e. image fidelity and watermark robustness, needed to be optimized simultaneously. By applying the multi-objective optimization algorithm, we can obtain a set of optimal solutions from which the user can select the most suitable one according to his demand without trial-and-error procedure.

The Bees Algorithm (BA) is a new population-based search algorithm. The algorithm mimics the food foraging behavior of swarms of honey bees. The foraging process begins in a colony by scout bees being sent to search for promising flower patches. Scout bees move randomly from one patch to another. When they return to the hive, those scout bees that found a patch will pass three pieces of information regarding that flower patch: the direction in which it will be found, its distance from the hive and its quality rating through the "waggle dance" [16]. This information helps the colony to evaluate the relative merit of different patches according to both the quality of the food they provide and the amount of energy needed to harvest it [17]. Accordingly, the bee colony can dispatch its bees to flower patches precisely. In [18], the Bees Algorithm was presented and its performance was tested by means of solving functional optimization problems, including nine benchmarking functions from two-dimensional function to ten-dimensional function, in terms of speed of optimization and accuracy of the results obtained. These experimental results show that the Bees Algorithm produces a 100% success rate in all cases. Compared with the deterministic simplex method [19], the stochastic simulated annealing optimization procedure [19], the GA [19] and the ant colony system [19], the BA can find the optima 1.4 times, 18.4 times, and 2.4 times faster than deterministic simplex method, GA, and ant colony system, respectively, in terms of averaged iteration number. The only exception is the stochastic simulated annealing optimization procedure, its speed is 2.5 times faster than BA. However, its success rate is lower. Generally speaking, the BA can outperform most popular optimization techniques compared with it in terms of speed of optimization and accuracy of the results obtained.

Recently, Pham and Ghanbarzadeh [20] extended the BA to solve multi-objective optimization problems, which is denoted as MOBA (multi-objective Bees Algorithm), and achieved very good performance. A standard mechanical design problem, the design of a welded beam structure, was used to benchmark the MOBA. In comparison with the number of solution found by non-dominated sorting genetic algorithms, it can be seen that the MOBA can find more non-dominated solutions fast. Based on the good performance for the MOBA in solving multi-objective optimization problems, we model the image watermarking problem via utilizing the MOBA to develop a new watermarking scheme. The cover image is transformed into DCT domain first. Initially, the watermark embedding locations are randomly selected to embed the watermark. The image fidelity and the robustness of the watermarked image are evaluated to form two objectives for the MOBA evolution and then the embedding locations are updated. These processes are repeated until convergence and a set of optimal solutions can be acquired. Each optimal solution corresponds to a specific set of embedding locations arrangement. Finally, the user can select one of the optimal solutions according to his demand.

This paper is organized as follows. We describe the fundamental concepts of multi-objective optimization and introduce the MOBA in Section 2. Section 3 explains the algorithm for embedding and extracting the watermark in the DCT domain with the MOBA. Section 4 illustrates the experimental results, and we also show the superiority of our scheme over the results by using the existing GA-based approaches in this section. In Section 5, the proposed method's applicability and weakness are explained and a comparison with another method which also handles conflicting requirements of watermarks is made. Finally, we conclude this paper in Section 6.

2 The MOBA

Since a minimum of a function f is a maximum of $-f$, the general optimization problem may be stated mathematically as maximize $f_i(\boldsymbol{x})$, $i = 1, 2, \ldots, l$, subject to Eqs. (1) to (2), where $\boldsymbol{x}$ is the column vector of n independent variables, i.e. $\boldsymbol{x} = [x_1, x_2, \ldots, x_n]^T$, $f_i(\boldsymbol{x})$ are the l objective functions, $c_j(\boldsymbol{x})$ are the p equality constraints, and $h_k(\boldsymbol{x})$ are the q inequality constraints. When $f_i(\boldsymbol{x})$ and Eqs. (1) and (2) are taken together, they are known as problem function [21].

$$c_j(x) = 0, \quad j = 1, 2, \ldots, p \tag{1}$$

$$h_k(x) \geq 0, \quad k = 1, 2, \ldots, q \tag{2}$$

The general multi-objective optimization tries to find the solution vectors in the solution space ***X*** which will satisfy the *p* equality constrains, the *q* inequality constraints, and will optimize the *l* objective functions. If all objective functions are for maximization, a feasible solution ***x*** is said to dominate another feasible solution ***y***, if and only if, $f_i(y) \leq f_i(x)$ for all *i* = *1, 2, ..., l* and $f_j(y) < f_j(x)$ for at least one objective function *j*. A solution is said to be Pareto optimal if it is not dominated by any other solution in the solution space. A Pareto optimal solution cannot be improved with respect to any objective without worsening at least one other objective. The set of all feasible non-dominated solutions in ***X*** is referred to as the Pareto optimal set, and for a given Pareto optimal set, the corresponding objective function values in the objective space are called the Pareto front.

The pseudo codes for the MOBA [20] is shown as follows.

step 1. Initialise population with random solutions.
step 2. Evaluate fitness of the population.
step 3. While (stopping criterion not met) //Forming new population.
step 4. Select sites for neighborhood search.
step 5. Determine the patch size.
step 6. Recruit bees for selected sites and evaluate fitnesses.
step 7. Select the representative bee from each patch.
step 8. Amend the Pareto optimal set.
step 9. Abandon sites without new information.
step 10. Assign remaining bees to search randomly and evaluate their fitnesses.
step 11. End While.

The algorithm requires a number of parameters to be set, such as number of scout bees, number of sites selected for neighborhood search, number of bees recruited for the selected sites, the initial size of each patch (a patch is a region in the search space that includes the visited site and its neighborhood), and the stopping criterion. The algorithm starts with *n* scout bees randomly distributed in the search space. The fitness of the sites visited by the scout bees are evaluated. The *m* non-dominated sites are designated as "selected sites" and chosen for neighborhood search. If the neighborhood search does not have any progress, the patch size is decreased. The algorithm searches around the selected sites. The representative bee will be the original one unless it is dominated by one of the recruited ones. If the representative is a non-dominated solution, it will be added to the Pareto optimal set. In the case when no improvement is gained the exploration of the patch is terminated. The remaining bees in the population are placed randomly around the search space to scout for new potential solutions. At the end of each iteration, the colony has two parts to its new population: representatives from the selected patches, and scout bees assigned to conduct random searches. These steps are repeated until a stopping criterion is met.

3 The Embedding and Extraction Methods

3.1 The Embedding Method

Let *I* be the original image with size $M \times N$ and *I** be the corresponding watermarked result. To embed watermark in the DCT domain, we transform *I* into DCT frequency bands by performing 8×8 block DCT on *I* first and get the coefficients in the frequency bands *D*,

$$D = DCT\,(I) \tag{3}$$

and

$$D = \bigcup_{m=1}^{M/8} \bigcup_{n=1}^{N/8} D_{(m,n)}. \tag{4}$$

For the *m*-th row and *n*-th column non-overlapping block with size 8×8 in *I* denoted as $I_{(m,n)}$, the resulting 64 DCT bands $D_{(m,n)}$ can be represented by

$$D_{(m,n)} = \bigcup_{k=0}^{63} \{D_{(m,n)}\,(k)\}, \quad 1 \leq \mathrm{m} \leq \frac{\mathrm{M}}{8}, \quad 1 \leq \mathrm{n} \leq \frac{\mathrm{N}}{8} \tag{5}$$

where $D_{(m,n)}(k)$ are zigzag ordered DCT coefficients. Let *W* be the embedded binary watermark with size $M_W \times N_W$. A pseudo-random number traversing method [22] is applied to permute the watermark *W* to dispel its spatial relationship. With a pre-determined key, k_0, in the pseudo-random number generating system, we have the scrambled watermark W_S. And, then W_S are embedded into the selected DCT frequency bands by using the embedding method.

Before introducing the embedding method, some embedding related terms are defined beforehand. The frequency set *F* taking both the imperceptibility and robustness requirements into account will be chosen to embed W_S by the MOBA. For each 8×8 non-overlapping DCT block (*m*, *n*), only the NUM_W frequency bands will be included in the frequency set $F_{(m,n)}$, which are then modified for watermark embedding. The definition of NUM_W is as follows:

$NUM_W = (128 \times M_W \times N_W \,/\, (M \times N))$.

In fact, the proposed MOBA-based algorithm can cooperate with any existing embedding strategies. To exhibit the good performance of the proposed algorithm, we adopt a simple swap-embedding method [23] instead of a sophisticated one, in which the watermark is embedded by modulating the relative value of two DCT coefficients within one DCT block. The watermark embedding method for block (*m*, *n*) is expressed as follows, in which $D_{(m,n)}(u)$ and $D_{(m,n)}(v) \in F_{(m,n)}$ and $u < v$.

for *i* = 1 *to* $\frac{1}{2}\mathrm{NUM}_W$ do

choose the i-th pair of DCT coefficients
$< D_{(m,n)}(u), D_{(m,n)}(v) >$
if $W_S(i) = 0$ then
if $D_{(m,n)}(u) > D_{(m,n)}(v)$ then
swap $D_{(m,n)}(u)$ and $D_{(m,n)}(v)$
end if
else
if $D_{(m,n)}(u) < D_{(m,n)}(v)$ then
swap $D_{(m,n)}(u)$ and $D_{(m,n)}(v)$
end if
end if
adjust both values so that

$$\left|D_{(m,n)}(u) - D_{(m,n)}(v)\right| > k$$

end for

The DCT coefficient $D_{(m,n)}(i)$ after watermark embedding is denoted as $D^*_{(m,n)}(i)$ and

$$D^* = \bigcup_{m=1}^{M/8} \bigcup_{n=1}^{N/8} \left\{D^*_{(m,n)}\right\} \tag{6}$$

where

$$D^*_{(m,n)} = \bigcup_{i=1}^{NUM_W} \left\{D^*_{(m,n)}(i)\right\} \tag{7}$$

And, we know that $D^*_{(m,n)}(i)$ equals to $D_{(m,n)}(i)$ if $i \notin F_{(m,n)}$.

Before executing the MOBA, the initial frequency set F is defined as

$$F = \bigcup_{m=1}^{M/8} \bigcup_{n=1}^{N/8} \left\{F_{(m,n)}(i)\,|_{i=1}^{NUM_W} = RS(D_{(m,n)}(k)\,|_{k=1}^{63})\right\} \tag{8}$$

where *RS*( ) is the random selection operator that randomly selects NUM_W frequency bands to embed W_S from the 63 AC coefficients in the DCT domain for each block. This randomly selected frequency bands, F, are encoded into scout bees by using the frequency indices, which also serves as the first step of the MOBA. For each scout bee conveying an assigned F, the corresponding fitness vector for that watermarked image consists of two components, i.e. the watermarked image fidelity and the robustness. The image fidelity was quantified by the PSNR of the watermarked image as defined in Eq. (9). As to the watermark robustness, in [14, 15], it was quantified by the averaged normalized cross-correlation (NC) for the pre-tested attacks. Such an averaged quantification way lurks a blind spot. We know that a satisfactorily averaged NC (*Avg_NC*) might be generated from some perfect NCs and some unsatisfactory ones. Thus, even an assigned F possesses high *Avg_NC*, still it can not guarantee that all the pre-tested attacks do not threat its robustness. A feasible approach to overcoming this problem is to adopt the minimum NC, *Min_NC*, rather than *Avg_NC* to qualify the watermark robustness. This approach can guarantee the lower bound of the watermark robustness for the pre-tested attacks. The related supporting evidence for the *Min_NC* qualification can be found in Section 4. Accordingly, in this paper, we adopt *Min_NC* to qualify the watermark robustness. The definition of the *Min_NC* is expressed in Eqs. (11) and (12), where NC_a is defined in Eq. (12) denote the extracted watermark and the corresponding NC value [24, 25] for the *a*th kind of attack. By applying the MOBA, those individuals (bees) possessing non-dominated fitness vectors in the Pareto optimal set are picked out. The user can then select one individual from those optimal individuals according to his demand for imperceptibility (PSNR) and robustness (*Min_NC*). And, the frequency bands F, encoded in this individual, are decoded. Subsequently, we designate the indices mapping between $F_{(m,n)}(i)$ and $D_{(m,n)}(k)$ as the secret key, k_1. The DCT coefficients D^* embedded by using the frequency bands F is reconstructed to an image by inverse DCT and denoted as I^*.

$$\mathrm{PSNR} = 10 \times \log_{10}\left(\frac{255^2}{\mathrm{MSE}}\right)(\mathrm{dB}) \tag{9}$$

$$MSE = \frac{1}{M \times N}\sum_{m=1}^{M}\sum_{n=1}^{N}\left(I(m,n) - I^*(m,n)\right)^2 \tag{10}$$

$$Min\_NC = \arg\min_{\mathrm{a}}\left(\mathrm{NC}_a\right) \tag{11}$$

$$\mathrm{NC_a} = \frac{\sum_{i=1}^{M_W}\sum_{j=1}^{N_w}[W(i,j)\times W_a(i,j)]}{\sum_{i=1}^{M_w}\sum_{j=1}^{N_w}[W(i,j)]^2} \times \frac{\sum_{i=1}^{M_W}\sum_{j=1}^{N_w}[(1-W(i,j))\times(1-W_a(i,j))]}{\sum_{i=1}^{M_w}\sum_{j=1}^{N_w}[1-W(i,j)]^2} \tag{12}$$

3.2 The Extraction Method

In extracting the watermarks, the original image I is not required. The optimized watermarked image might incur some intentional or unintentional attack, and the resulting image after attack is denoted as $\tilde{I}$. The DCT coefficients of $\tilde{I}$ represented as $\tilde{D}$ are computed. Integrating $\tilde{D}$ with the secret key k_1 corresponding to the embedded frequency set F, we can estimate W_S by using the reverse process of watermark embedding. And, the estimated W_S is denoted as $\tilde{W}_S$. Finally, we utilize the secret key k_0 to re-permute $\tilde{W}_S$ to acquire the embedded watermark $\tilde{W}$.

4 The Experimental Results

To verify the performance of the proposed watermarking scheme three experiments adopting the image-type watermark were conducted. In these experiments, the size of the cover image is 256 $\times$ 256 and the size of the

(a) (b) (c)

Fig. 1: (a) The watermark image; (b) Lena image; (c) F-16 image.

watermark is 32 × 32 as shown in figure 1(a). Hence, the number of bits to be modified in each 8 × 8 non-overlapping block, i.e. NUM_W, is 2.

The first experiment was used to show the suitability of adopting *Min_NC* rather than *Avg_NC* to qualify the watermark robustness. We take the Lena image in figure 1(b) as an example. We apply five pre-tested attacks namely LPF, sharpening, median filtering (MF), JPEG compression with quality factor 80%, and 25% cropping. Figure 2 shows the searched Pareto optimal sets by using *Min_NC* and *Avg_NC* as the representative watermark robustness, respectively. We choose one optimal solution pair, (*Avg_NC_OP*, *Min_NC_OP*) from the sets on the basis of possessing similar *PSNRs*. The extracted watermarks and the corresponding NCs for the pre-tested attacks by using *Avg_NC_OP*and *Min_NC_OP* are shown in Tables 1 and 2, respectively. The most noticeable point is that the lower-bound NC using *Min_NC_OP* is 0.8463 that is superior to 0.8261 using *Avg_NC_OP*. Figure 3 shows the searched Pareto optimal sets for figure 1(c) by using *Min_NC* and *Avg_NC* as the representative watermark robustness, respectively. We choose one optimal solution pair, (*Avg_NC_OP*, *Min_NC_OP*) from the sets on the basis of possessing similar PSNRs. Tables 3 and 4 show he extracted watermarks and the corresponding NCs for the pre-tested attacks by using *Avg_NC_OP*and *Min_NC_OP*, respectively. We can also find that the lower-bound *NC* using *Min_NC_OP* is 0.9356 that is superior to 0.9110 using *Avg_NC_OP*. In fact, by our test the predominance property of *Min_NC* all applies to the test data. These results support the use of *Min_NC* to replace *Avg_NC* for qualifying the watermark robustness.

The second experiment was conducted to demonstrate the performance of the proposed MOBA-based watermarking scheme by using two cover images (figure 1(b) and (c)). The five pre- tested attacks are the same as the first experiment. The kinds and number of the pre-tested attacks can be changed according to the user's demand. The resulting PSNRs of the watermarked image and the *Min_NCs* after attacking construct the fitness vectors, i.e. the objectives for the MOBA. The related parameters of the MOBA were set as follows. The

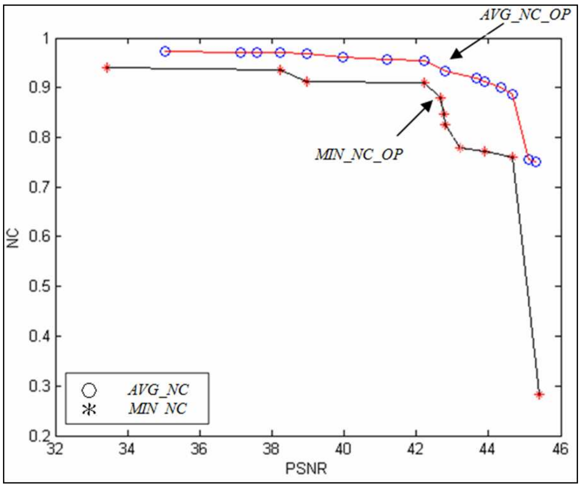
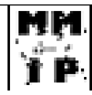
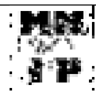
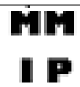
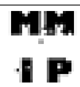
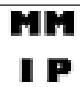


Fig. 2: The searched Pareto optimal sets for figure 1(b) by using *Min_NC* and *Avg_NC* as the representative watermark robustness, respectively.

Table 1: The extracted watermarks and the corresponding NCs for the pre-tested attacks by applying *Avg_NC_OP* to figure 1(b).

Attacks	Extracted Watermarks	NCs
LPF		0.8612
MF		0.8261
JPEG		0.9987
Sharpening		0.9760
Cropping		1

number of scout bees is 10, the number of sites selected for neighborhood search is 20, number of bees recruited for the selected sites is 3, the initial size of each patch is 5, and the maximum iteration number is 100.

For the Lena image (figure 1(b)), via the MOBA evolution, we obtain the optimal set of the watermarked images labeled by 'o' in figure 4. Compared with the best results using the GA-based approaches [14, 15], which are designated by '*' and '△' in figure 4, it can be noted that our method provide several solutions that can dominate those of the GA-based methods. That is, our method can find solutions superior to those solved by using Shieh's and Wei's approaches [14, 15]. For the F-16 image (figure

Table 2: The extracted watermarks and the corresponding NCs for the pre-tested attacks by applying *Min_NC_OP* to figure 1(b).

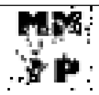
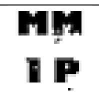
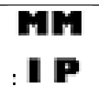
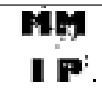
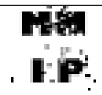
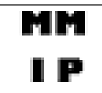
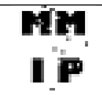
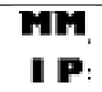
Attacks	Extracted Watermarks	NCs
LPF		0.9383
MF		0.8463
JPEG		0.9424
Sharpening		0.9710
Cropping		0.9974

Table 3: The extracted watermarks and the corresponding NCs for the pre-tested attacks by applying *Avg_NC_OP* to figure 1(c).

Attacks	Extracted Watermarks	NCs
LPF		0.9683
MF		0.9110
JPEG		1
Sharpening		0.9671
Cropping		0.9934

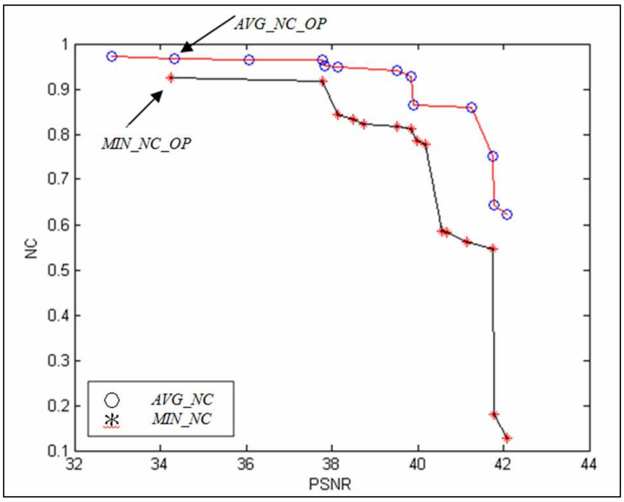
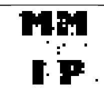
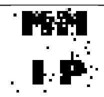
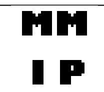
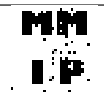
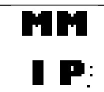


Fig. 3: The searched Pareto optimal sets for figure 1(c) by using *Min_NC* and *Avg_NC* as the representative watermark robustness, respectively.

Table 4: The extracted watermarks and the corresponding NCs for the pre-tested attacks by applying *Min_NC_OP* to figure 1(c).

Attacks	Extracted Watermarks	NCs
LPF		0.9620
MF		0.9356
JPEG		1
Sharpening		0.9478
Cropping		0.9960

1(c)), via the MOBA evolution, we obtain the optimal set of the watermarked images labeled by ‘o’ in figure 5. The best results using the GA-based approaches [14, 15] are designated by ‘*’ and typo in figure 5, it can also be noted that our method provide solution that can dominate those of the GA-based methods.

The proposed performance enhancement scheme can be employed to enhance various existing transform-domain watermarking methods. In order to justify the performance enhancement capability, a simple swap-embedding scheme, originally introduced in [23], was used in this paper to evaluate the performance of the proposed enhancement method. The swap-embedding scheme is inherently vulnerable to geometric distortion, such as StirMark attack, because of disturbing the synchronization between the watermark embedding and extraction. Hence, the average NC value of the extracted watermarks after StirMark attacks can just be promoted by 0.2, from original 0.1 to 0.3, when our scheme was employed. To overcome this problem, we plan to correct the geometric distortion via feature-based registration before watermark extraction in our future study.

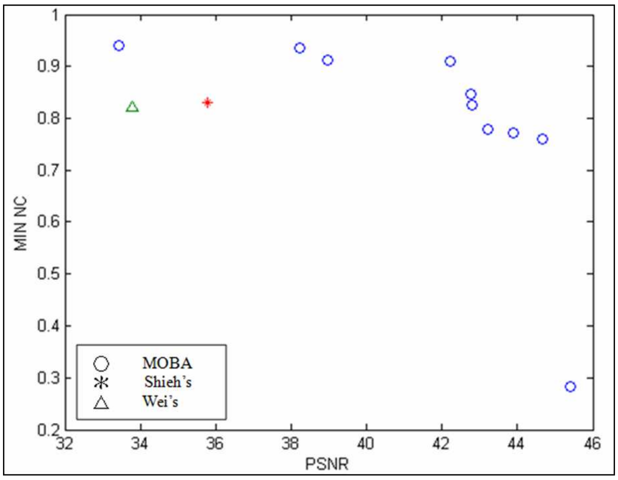


Fig. 4: The searched optimal results for figure 1(b) by using our MOBA scheme, Shieh's method [14], and Wei's method [15].

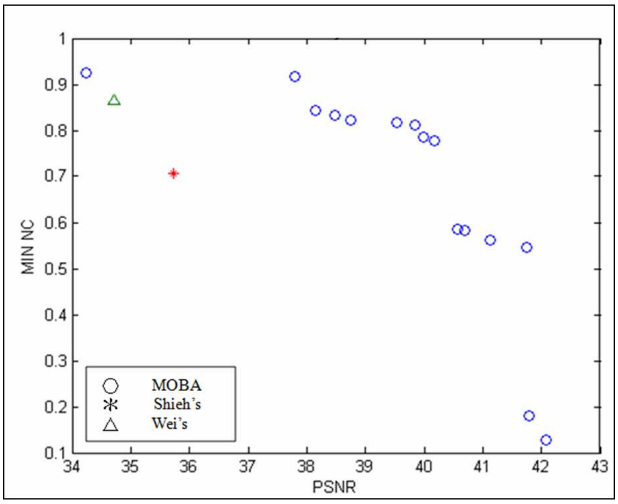


Fig. 5: The searched optimal results for figure 1(c) by using our MOBA scheme, Shieh's method [14], and Wei's method [15].

5 Discussions

Recently, problem about handling conflicting requirements of watermarks with GAs has also been addressed by Huang et al. [26]. Their approach was based on a preset fidelity constraint, which is a user-specified acceptable fidelity, to model the detection robustness as a single objective function and then utilized GA to find better embedding results. This approach seems to be able to solve the plight encountered by the existing SGA methods [14, 15] that they must consider the weights between both the objectives. However, in fact, the problem still exists, it just emerges in another appearance. First, the user might have no idea about how to specify the moderate fidelity. If the fidelity is over-setting, the corresponding robustness might be insufficient. On the contrary, the visual quality of the watermarked result might be unacceptable, if the fidelity is under-setting. Accordingly, a trial-and-error process for setting a moderate fidelity is unavoidable and it is inconvenient for users. Furthermore, their approach still implicitly face a predicament about how to decide the two parameters, β_1 andβ_2 in the fitness function value F, which will affect the system robustness. Contrast with Huang's approach [26], our scheme can provide users a set of solutions and then a satisfactory one is chosen from such that there is no need of a trial-and-error procedure.

The proposed MOBA-based scheme can be regarded as an informed-embedding watermarking scheme because the embedder utilizes the available aiding information during the embedding stage. A general-purpose watermarking scheme is supposed to be robust against many types of general attacks. Since its performance for unconsidered attacks is not enhanced, the feasibility of our watermarking scheme is limited. However, there is a digital watermarking application, i.e. steganography, in which all applicable attacks are supposed to be predictable and even controllable for the embedder. For steganographic applications, only the host-interference and optional lossy compressions shall be considered. The degree of lossy compression applied to the cover content can even be controlled by the sender of secret messages. Therefore, the proposed watermarking scheme can be very useful for steganographic applications.

6 Conclusions

Optimizing watermarked image fidelity and robustness is an attractive research topic in image watermarking. The existing GA-based approaches try to achieve this goal by linearly combining the two goals into a single objective and then search the optimal solution by using the genetic algorithm. In fact, watermarked image fidelity and robustness are two conflicting goals. The existing GA-based methods suffer from the performance fluctuation with respect to the weight setting. In this paper, we propose a robust watermarking algorithm using MOBA. This approach will not only provide robustness but also provide good fidelity for image watermarking. In comparison with the existing GA-based methods, this proposed multi-objective optimization scheme can get better visual quality in the watermarked images and higher NCs in the extracted watermarks. In addition, the proposed MOBA-based watermarking scheme can also provide solutions with higher stability.

Acknowledgements

This work was partially supported by the National Science Council under grant number NSC 97-2221-E-024-009-MY3.

References

[1] H.H. Tsai and J.S. Cheng, Adaptive signal-dependent audio watermarking based on human auditory system and neural networks, Applied Intelligence, **3**, 191-206 (2005).

[2] M. Alghoniemy, A.H. Tewfik, Geometric Invariance in image watermarking, IEEE Transactions on Image Processing, **13**, 145-153 (2004).

[3] P. Bao, M. Xiaohu, Image adaptive watermarking using wavelet domain singular value decomposition, IEEE Transactions on Circuits and Systems for Video Technology, **15**, 96-102 (2005).

[4] M. Barni, F. Bartolini, A. Piva, Multichannel watermarking of color images, IEEE Transactions on Circuits and Systems for Video Technology, **12**, 142-156 (2002).

[5] P.M. Chen, A robust digital watermarking based on a statistic approach. In Proc. of IEEE Int. Conf. on Information Technology: Coding and Computing, 116-121 (2000).

[6] C.H. Chou and Y.C. Li, A perceptually tuned subband image coder based on the measure of just-noticeable-distortion profile, IEEE Transactions on Circuit and Systems for Video Technology, **5**, 467-476 (1995).

[7] I.J. Cox, M.L. Miller, The first 50 years of electronic watermarking, Journal of Applied Signal Processing, **2**, 126-132 (2002).

[8] K. Deb, Multi-Objective Optimization using Evolutionary Algorithms, Wiley, (2001).

[9] H. Guo, Y. Li, A. Liu, S. Jajodi, A fragile watermarking scheme for detecting malicious modifications of database relations, Information Science, **176**, 1350-1378 (2006).

[10] Y.C. Hou, P.M. Chen, Y.F. Chiao, Steganography: An efficient data hiding method. In Proc. of *CVPRIP'98*, **4**, 211-214 (1998).

[11] T.M. Ng, H.K. Garg, Maximum-likelihood detection in DWT domain image watermarking using Laplacian modeling, IEEE Signal Processing Letters, **12**, 285-288 (2005).

[12] C.T. Hsu, J.L. Wu, Hidden digital watermarks in images, IEEE Transactions on Image Process, **1**, 58-68 (1999).

[13] P.H. W. Wong, O.C. Au, A capacity estimation technique for JPEG-to-JPEG image watermarking, IEEE Transactions on Circuits and Systems for Video Technology, **13**, 746-752 (2003).

[14] C.S. Shieh, H.C. Huang, F.H. Wang, J.S. Pan, Genetic watermarking based on transform-domain techniques, Pattern Recognition, **37**, 555-565 (2004).

[15] Z. Wei, J. Dai, J. Li, Genetic watermarking based on DCT domain techniques. In Proc. of IEEE CCECE/CCGEI, 2365-2368 (2006).

[16] V. Frisch, Bees: their vision, chemical senses and language, Cornell University Press, (1976).

[17] S. Camazine, J. Deneubourg, N.R. Franks, J. Sneyd, G. Theraula and E. Bonabeau, Self-organization in biological systems, Princeton University Press, (2003).

[18] D.T. Pham, A. Ghanbarzadeh, E. Koc, S. Otri, S. Rahim, M. Zaidi, The Bees Algorithm-a novel tool for complex optimisation problems. In Proc. of 2nd Int. Virtual Conf. on Intelligent Production Machines and Systems, 454-459 (2006).

[19] M. Mathur, S.B. Karale, S. Priye, V.K. Jayaraman and B.D. Kulkarni, Ant colony approach to continuous function optimization, Ind. Eng. Chem. Res., **39**, 3814-3822 (2000).

[20] D.T. Pham, A. Ghanbarzadeh, Multi-Objective Optimisation using the Bees Algorithm, Proceedings of IPROMS, 100-104 (2007).

[21] K. Deb, Multi-Objective Optimization using Evolutionary Algorithms, Chichester, Wiley, (2001).

[22] F.A.P. Petitcolas, R.J. Anderson, M.G. Kuhn, Information hiding—a survey. In Proc. of IEEE, **7**, 1062–1078 (1999).

[23] C. Shoemaker, "Hidden bits: A survey of techniques for digital watermarking," 2002. [Online] available: http://www.vu.union.edu/~{}shoemakc/watermarking/watermarking.htm.

[24] Y. C. Hou, P. M. Chen, Y. F. Chiao, Steganography: an efficient data hiding method. In Proc. of CVPRIP, **4**, 211-214 (1998).

[25] P. M. Chen, A robust digital watermarking based on a statistic approach, IEEE Int. Conf. on Information Technology: Coding and Computing, 116-121 (2000).

[26] C.H. Huang and J.L. Wua, Fidelity-guaranteed robustness enhancement of blind-detection watermarking schemes, Information Sciences, **179**, 791-808 (2009).

Jiann-Shu Lee received the Ph.D. degree in electrical engineering from the National Cheng Kung University, Tainan, Taiwan. He is currently a Professor with the Department of Computer Science and Information Engineering, National University of Tainan, Taiwan. His current research interests include multimedia signal analysis, image processing, medical image processing, and computational intelligence. He is author or coauthor of many academic articles. Dr. Lee has engaged as a Section Chairs in many domestic and international conferences. He has also received numerous awards from organizations, such as Acer, International Association for the Engineers, Information Hiding and Multimedia Signal Processing, and Xerox.

Jing-Wein Wang received B.S. and M.S. degrees in Electronic Engineering from National Taiwan University of Science and Technology in 1986 and 1988, respectively, and a Ph.D. degree in Electrical Engineering from National Cheng Kung University, Taiwan, in 1998. From 1992 to 2000 he was a principal project leader at Equipment Design Center of PHILIPS, Taiwan. In 2000, he joined the faculty of National Kaohsiung University of Applied Sciences, where he is currently a professor in the Institute of Photonics and Communications. His current research interests are combinatorial optimization, pattern recognition, wavelets, and biometric applications. He is a member of IEEE.

Kuang-Yu Chien received the Master degree in Department of Computer Science and Information Engineering from National University of Tainan, Tainan, Taiwan, in 2009. His research interests include softwae formal methods and image processing.