HYBRID OF PARTICLE SWARM OPTIMIZATION WITH EVOLUTIONARY OPERATORS TO FRAGILE IMAGE WATERMARKING BASED DCT

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ABSTRACT

Particle swarm optimization (PSO) is a new promising evolutionary algorithm for the optimization and search problem. One problem of PSO is its tendency to trap into local optima due to its mechanism in information sharing. This paper proposes a novel hybrid PSO, namely (HPSO) technique by merging both a mutation operator and natural selection to solve the problem of premature convergence. By introducing Cauchy mutation and evolutionary selection strategy based on roulette wheel selection, HPSO could greatly reduce the probability of trapping into local optimum. HPSO is proposed to improve the performance of fragile watermarking based DCT *which results in enhancing both the quality of the watermarked image and the extracted watermark. After embedding watermark to the original image in the frequency domain, the conversion of real numbers of the modified coefficients in frequency domain to integer numbers in spatial domain produces some rounding errors problem. This problem results in completely different of the extracted watermark from the embedded watermark. The new developed PSO with evolutionary operators is carried out for correcting the rounding errors by training a translation map used to modify the inverse DCT (IDCT) coefficients from real to integer numbers. The experimental results show the superiority of the proposed algorithm comparing with the standard PSO for improving the performance of DCT fragile watermarking. Besides, it has been shown that the developed PSO is faster in convergence and the obtained results proved to have higher fitness than the other algorithm.*

KEYWORDS

Particle Swarm Optimization, Evolutionary Operators, DCT fragile watermarking

1. INTRODUCTION

With the widespread use of the Internet and the development in computer industry, the digital media including images, audio, and video are easily acquired in our daily life. Digital multimedia content suffers from infringing upon the copyrights by duplication or easy modification. As a result, data piracy has become a serious issue. To solve this problem, some copyright protection schemes have been proposed. One of the most important techniques used for copyright protection is digital image watermarking. Digital watermarking is one way to embed secret information, or watermark into the original image to protect the ownership or to hide secret information [1–3]. Watermarking schemes can be categorized as visible and invisible. Visible watermarks are visual patterns like logo that appears on one side of an image [4]. These watermarks are easily identified, and consequently can be easily removed from the original images. Invisible watermarks [5] are more secure and roust than visible watermarks. This is because the embedding locations are secret and only the authorized persons with secret keys can extract the secret watermarks. In case of invisible watermarking, the watermarked image should look similar to the original one and should not cause suspicion to others.

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Digital watermarking can be also categorized as robust and fragile [6]. Robust watermarking can resists some image manipulation called attacks which leads to detect the watermark after image manipulation operations. In this case, the extracted watermarks should be highly correlated with the embedded ones. In other words, the extracted watermarks should be recognizable in case of robust watermarking system. Fragile watermarking on the other hand, becomes invalid after even the slightest modification of the watermarked image, and does not resist to intentional and unintentional attacks. Fragile watermarks are mainly used for authentication. Fragile watermarking techniques can be applied in the spatial domain or the frequency domain. In spatial domain, watermarks are embedded by modifying the pixel value directly [7-9]. The advantages of using the spatial domain is that its application is done easily, however, the main disadvantages of this technique are the easiness of bypassing the security they provide [10, 11] and the damage occurs to the watermark due to the lossy compression of image [12]. On the other hand, in the frequency domain, watermarks can be embedded by modifying the transform coefficient of Discrete Cosine transform (DCT) [13-17] and Discrete Wavelet transform [18,19]. The main advantages of using the frequency domain are that they can easily be adapted to lossy compression.

In DCT based fragile watermarking, the host image is first transformed into its frequency domain. Then the watermarks are generally embedded by modifying the least significant bits (LSB) of the frequency domain coefficients. After the embedding process is completed, rounding the real numbers of the modified IDCT coefficients to integer numbers results in completely different between the extracted watermark and the embedded one and reduces the watermarked image quality. In recent years, artificial intelligence techniques such as genetic algorithm (GA), genetic programming, clonal selection algorithm (CSA), particle swarm optimization (PSO), and differential evolution (DE) were introduced for improving the performance of digital watermarking, but there are a few studies to reduce the rounding error of DCT based fragile watermarking techniques. In [20] GA was used to find a guiding bit map for the whole host image, this guiding bit map directs the value of the pixels and replaces the rounding operation by the truncation process for each pixel in the block image. The effectiveness of this process depends on guiding bit map. In [21], a heuristic method was proposed to enhance the quality of the extracted watermark, the pixel values are modified by using the reference coefficient data. The obtained results in terms of Normalized cross Correlation (NC) is not equal 1 with the methods proposed in the previous literature. In [22] intelligent optimization algorithms such as GA, DE, standard PSO, and CSA were applied to correct the rounding errors, and the performance of them were compared in terms of quality and convergence rate. The experimental results show that GA, DE and PSO appeared to have similar performance, on the other hand CSA produced better PSNR results but with higher time computation compared to the other algorithms. In this paper we concerned with the development of the standard PSO to solve the rounding error problem of fragile watermarking based DCT.

2. RELATED WORK

PSO algorithm seems to be a promising approach for different types of the optimization problems. It is simple and easy to realize in comparison with other computation intelligence techniques. It is received widely attention from evolutionary field and has become a hot spot of research. Although PSO has a highly speed of convergence, many literatures have shown that PSO has a difficulty to jump out of the local optima if it is fall into local minima. In literature, many approaches have been introduced to improve the performance of the standard PSO, by merging PSO with other evolutionary computation techniques. In [23] a hybrid method combining two heuristic optimization techniques, GA and PSO has developed for the global optimization of multimodal functions. The work in [24], obtained better results by applying

PSO first followed by applying GA in their profiled corrugated horn antenna optimization problem. The effort in [25] has introduced a new integrated genetic swarm optimization algorithm (IGSA), combining the strengths of PSO with GA. It is applied in the tuning of PID controllers for the ball and hoop system. A genetic programming based adaptable evolutionary hybrid particle swarm optimization algorithm, have presented in [26], for avoiding premature convergence to local minima by the introduction of diversity in the swarm.

In addition to incorporate evolutionary algorithms into PSO, another research trend is to merge evolutionary operators like selection, mutation, and crossover to PSO. Selection operation used with PSO selects the best performance particles and keeps them to the next generation [27]. In crossover operation, information between two individuals can be exchanged to form new individuals have the ability to extend the search area as that in evolutionary programming and GAs [28]. The most common operator that has been applied to PSO is the mutation operators. Ratnaweera et. al.[29] conclude that the particles are close to the local optima due to lack of population diversity in PSO algorithms. Therefore, applying mutation operator to PSO should enhance the capacity of its global search and consequently improve its performance. Therefore, the main advantages of adding mutation operator to PSO are to increase both the diversity of the population and the ability of particles to be far away from the local minima. One approach is to mutate parameters such as the position of the neighborhood best, as well as the inertia weight [30]. In literature [31], the locations of particles are rearranged when the particles are near to each other to keep the diversity and consequently the particles can escape from falling into local minima. In [32], two mechanisms; collision and avoiding are designed to prevent particle from colliding with each other and therefore increase the diversity of the population. The first model of Particle swarms using the quantum model (QPSO) was introduced by Sun et.al. [33], which rather than using the standard position and velocity to describe the particles, a wave function is used. In their studies [34] each of the global best particle value and the mean value of all particles' previous best position is respectively mutated with Cauchy distribution, and the results show that the performance of QPSO with mutation is better than PSO alone. R. A. Krohling et.al. in [35,36] show that the performance of the standard PSO can be improved using Gaussian and Cauchy probability distribution. Recently, evolutionary programming with exponential mutation has also been proposed [37].

In this paper we propose the hybrid of PSO with Cauchy mutation and natural selection strategy based on roulette wheel selection to reduce its tendency of trapping into local minima and overcome the premature convergence of the standard PSO. The main idea of merging Cauchy operator to PSO is that the variance of Cauchy distribution is infinite and consequently, it is good in the global search for its long jump ability, and helpful in produces the diversity. The proposed algorithm is carried out for correcting the rounding error problem in fragile watermarking based DCT, besides the performance of the proposed method is compared with the standard PSO. The proposed method is superior to the methods described in the previous literature in terms of NC and PSNR of the watermark image. Comparing with the previous methods [20, 21], NC value is near to one with lower number of iterations, and PSNR is higher comparing to the method used in [22].

The paper is organized as follows: section 3 introduces the fundamental concept of PSO, the two evolutionary operators merged with the standard PSO, and the framework of the proposed algorithm. Section 4 demonstrates the principles of fragile watermarking based DCT method. Pseudo code of HPSO algorithm for solving the rounded error problem was introduced in section 5. Section 6 describes the simulation results. Finally, section 7 concludes the whole work.

3. FUNDAMENTALS CONCEPT OF PSO

Kennedy and Eberhart were the first ones to introduce PSO [38]. It is motivated from the social behavior of organism such as bird flocking or fish schooling. It attempts to mimic the natural process of group communication in a wide range of domains and can be used to solve many different problems. Like other evolutionary algorithms, PSO is also a population-based search algorithm and initializes with a population of randomly generated solutions called particles which fly through the search space by updating the generation. Each particle represents a candidate solution to the optimization problem, and has a velocity and a position. The position of a particle is affected by both the best position visited by it and the position of the best particle in its neighbourhood. The best particle in the population is denoted by global best (gbest), while the best position that has been visited by the current particle is denoted by local best (pbest). Each particle is updated using the following equations:

$$v_i(n+1) = w_i v_i(n) + c_1 rand_1()(pbest - x_i(n)) + c_2 rand_2()(gbest - x_i(n)) \quad (1)$$

$$x_i(n+1) = x_i(n) + v_i(n+1) \quad (2)$$

Where:

$x_i(n+1)$ and $x_i(n)$ represent the current and the previous positions of particle i

$v_i(n+1)$ and $v_i(n)$ are the current and the previous velocity of the particle i.

$rand_1$ and $rand_2$ are random numbers uniformly distributed within [0,1].

W is an inertia weight which controls the momentum of the particle.

In typical implementations of PSO algorithm, the value of w_i is decreased linearly from 1.0 to near 0 in each iteration. Commonly the inertia weight is set according to the following equation:

$$w_i = w_{\max} - \frac{w_{\max} - w_{\min}}{iter_{\max}} \cdot iter \quad (3)$$

Where: $iter_{\max}$ is the maximum number of iterations, and $iter$ is the current number of iterations [ref]. Each particle in PSO shares the information with its neighbors. The updating equations 1 and 2 combine both of the cognition component of each particle and the social component of all the particles in a group. Although the speed of convergence is very fast, many experiments have shown that once PSO traps into local optimum, it is difficult for PSO to jump out of the local optimum [fast particle].

In this paper, we propose merging PSO with Cauchy mutation operator in addition to roulette wheel selection to prevent PSO from falling in a local optimum; the hybrid algorithm is so called HPSO. The variance of Cauchy distribution is infinite due to the non existence of expectation of Cauchy distribution. In [39] Cauchy mutation operator proves to be good at the global search as a result of its long jump ability. This paper shows that the Cauchy mutation is helpful in combining with PSO as well. In addition to Cauchy mutation operator, PSO uses the natural selection strategy as used in evolutionary programming to select the best particles and eliminate the bad ones. This paper proves that the proposed HPSO to the fragile watermarking in DCT domain has: fast speed to reach to the best solution, the ability to make particles escape from falling in local optima, and finally has the ability to enhance both NC and PSNR with minimum number of iterations comparing with using PSO alone. Cauchy mutation, natural selection, and HPSO algorithm are depicted in the next paragraph.

3.1. Cauchy Mutation

To overcome the weakness of PSO, the Cauchy mutation is incorporated into PSO algorithm. The basic idea is that the velocity and position of a particle are updated not only according to equations (1) and (2), but also according to Cauchy mutation as follows:

$$v_i(n+1) = v_i(n)\exp(\delta) \tag{4}$$

$$x_i(n+1) = x_i(n) + v_i(n+1)\delta_i \tag{5}$$

Where: δ and δ_i denote Cauchy random numbers.

Since the expectation of Cauchy distribution doesn't exist, the variance of Cauchy distribution is infinite so that the Cauchy mutation could make a particle have a long jump. By adding the update equations of (4) and (5), PSO greatly increase the probability of escaping from the local optimum.

3.2. Roulette Wheel Selection

In the standard PSO, all parents are directly replaced by their offspring no matter whether they have better performance than their parents or not. Particle is always replaced by its offspring either it moves to the best or worse position. In fact, the most particles fly to the worse positions for most cases; therefore the whole swarm will converge on local optima. In this paper, we introduce an evolution selection strategy based on roulette wheel selection to PSO like the evolutionary algorithms, in which each particle survives according to a selection rule. Therefore, the particle's position at the next generation is not only due to the position update but also to the evolution selection. By this strategy, PSO could greatly reduce the probability of trapping into local optima.

The evolutionary selection strategy based on roulette wheel is carried out as follows. Instead of comparing each parent particles with the corresponding offspring particles generated from comparing the two updating equations, union the parents with the offspring in one population to select the best one. Then, all particles are mapped to contiguous segments of a line, such that each particle's segment is equal in size to its fitness. Particles are selected according to their fitness. The better the particles are those with bigger fitness and have the more chances to be selected. Finally, a random number is generated and the particle whose segment spans the random number is selected. The process is repeated until the desired number of particles is obtained.

The framework of the Roulette wheel selection:

1. First compute the probability of selection for each particle
2. Generate random number (r) between interval [0,1]
3. Loop through the individual if r is $\succ$ probability of selection for the current particle, and less than the probability of selection for the next particle, return the current particle.

3.3. Framework of HPSO Algorithm

The major steps of HPSO are as follows:

Step1: The initial population is formed by randomly generating the position and velocity for each particle.

Step2: Evaluate each particle's fitness.

Step3: If the fitness of the current particle is smaller than its previous best (pbest) fitness, replace pbest by the update pbest.

Step4: For each particle, if its fitness is smaller than the best one (gbest) of all the particles, update gbest.

Step5: Apply the following operations to each particle;

(1) According to the formula (1) and (2), form a new particle t.

(2) Form a new particle t' according to the formula (4) and (5).

(3) Compare t with t' and then chose the one with smaller fitness to be the offspring.

Step6: Generate the next generation using the above evolutionary selection strategy.

Step7: if the stop criterion is satisfied, then stop, else go to Step 3.

4. PRINCIPLES OF FRAGILE WATERMARKING BASED DCT

Let Y and W represent the original image and the watermark image with sizes M×N and $M_w \times N_w$ respectively. We explain the rounding error problem after embedding using example of four watermark bits embedded in 8×8 DCT block of host image. The most important consideration is to select the best locations for watermark embedding in frequency domain [40]. The selected locations for embedding the watermark in each DCT block of Y are: $(3,1)$, $(2,2)$, $(1,3)$, and $(1,4)$ respectively as in [20]. The least significant bit (LSB) modification is used in embedding the watermark to the host image in this paper.

The process of embedding watermark into DCT frequency bands of Y is described as follows:

- First, the host image is divided into 8×8 non overlapping blocks as given below:

$$Y = \bigcup_{m=1}^{M/8} \bigcup_{n=1}^{N/8} Y_{(m,n)} \tag{6}$$

- The spatial domain pixels of each block in Y are transformed into DCT domain as follows:

$$Y_{(m,n)}^{DCT} = DCT(Y_{(m,n)}) \tag{7}$$

- The watermark is embedded into the integer part of the absolute real number of $Y_{(m,n)}^{DCT}$ so as to obtain $Y_{(m,n)}^{WDCT}$.
- Apply the inverse DCT to $Y_{(m,n)}^{WDCT}$ so as to obtain $Y_{(m,n)}^{WR}$, which is the watermarked image block with real numbers.
- Finally, all the real numbers of $Y_{(m,n)}^{WR}$ are rounded to the integers and the watermarked image block $Y_{(m,n)}^{W}$ is obtained.

The watermark extraction is described as follows:

- The watermarked image is divided into 8×8 image blocks, and DCT performed for each block
- The integer parts of the absolute values belonging to the specific positions of the embedded watermark of DCT domain are obtained.
- The decimal values are translated into the binary format.
- Finally, LSB of the obtained binary values reveal the watermark.

Rounding real numbers of IDCT coefficients into integers in embedding process produces watermark image different from the embedded watermark image. Figures 1-2 show examples of host image block with the specific locations of embedding, and the watermark image block. The extracted watermark image block [0 0 0 1] which is different from the embedded [1 1 1 0] due to the rounding error is shown in figure 3.

218	29	4	66	176	111	31	73
32	170	72	42	113	155	255	39
146	197	20	84	33	138	154	142
170	162	118	75	17	94	89	58
0	115	39	244	40	224	81	169
232	52	99	240	4	96	243	252
39	188	211	8	92	226	61	251
143	40	116	36	27	196	9	62

Figure1. Intensity value of the original image block

		1	0				
	1						
1							

Figure 2. The binary watermark image block

		0	1				
	0						
0							

Figure 3. Extracted watermarked image block

We introduce the HPSO to round the real numbers of the modified IDCT coefficients to integers instead of using the simple rounded technique as described in the next paragraph.

5. PSEUDO CODE OF HPSO BASED FRAGILE WATERMARKING

In order to solve the problem of rounding error, HPSO algorithm is employed to achieve a suitable solution for translating the real numbers into the integers. HPSO based watermark embedding technique is described as follows:

1. Divide the host image into 8×8 image block:

$$Y = \bigcup_{m=1}^{M/8} \bigcup_{n=1}^{N/8} Y_{(m,n)} \tag{8}$$

2. Perform DCT to each block of the host image

$$Y_{(m,n)}^{DCT} = \mathrm{DCT}\,(Y_{(m,n)}) \tag{9}$$

3. Divide watermark image into 2×2 blocks

$$W = \bigcup_{m=1}^{M_w/2} \bigcup_{n=1}^{N_w/2} W_{(m,n)} \tag{10}$$

4. Embed the watermark block into the coefficients of $Y_{(m,n)}^{DCT}$

$$Y_{(m,n)}^{WDCT} = W_{(m,n)} \oplus Y_{(m,n)}^{DCT} \tag{11}$$

5. Compute inverse DCT of $Y_{(m,n)}^{WDCT}$ to obtain the watermarked image

$$Y_{(m,n)}^{WR} = \text{IDCT}(Y_{(m,n)}^{WDCT}) \tag{12}$$

6. Round the real numbers of $Y_{(m,n)}^{WR}$ using HPSO

$$Y_{(m,n)}^{WHPSO} = \text{HPSO}(Y_{(m,n)}^{WR}) \tag{13}$$

7. Repeat steps from 3 to 6 for all blocks.

HPSO rounds the real numbers of the modified IDCT coefficients to integers using a solution set that constitute a translation map. The elements of the map are trained by HPSO as described in the following paragraph.

5.1. HPSO Algorithm Based Watermarking for Solving the Rounding Problem

In general, HPSO algorithm is initialized with a group of random particles that form initial population. Each particle in the population corresponds to a solution which is evaluated by a fitness function. The process will repeat for many times until a constant number of iterations are reached. Applying HPSO algorithm to solve the rounding problem, the particle or a solution set P, consisting of eight real numbers is represented as: $P = p_1, p_2, p_3, p_4, p_5, p_6, p_7, p_8$. Integer parts of this solution set are then encoded in binary having 64 bits for evaluating the constraint and fitness values. A sample of solutions sets and its binary coding that form a translation map are shown in figures 4 and 5.

p_1	31.1
p_2	61.9
p_3	194.1
p_4	4.27
p_5	0.01
p_6	92.05
p_7	236.43
p_8	254.81

Figure 4. Solution set of PSO

0	0	0	1	1	1	1	1
0	0	1	1	1	1	1	0
1	1	0	0	0	0	1	0
0	0	0	0	0	1	0	0
0	0	0	0	0	0	0	0
0	1	0	1	1	1	0	0
1	1	1	0	1	1	0	0
1	1	1	1	1	1	1	1

Figure 5. Translation map of P solutions in binary form

The binary elements of the translation map are used for translating the real numbers into integers using the rules given below:

(1) $Y_{(m,n)}^{WHPSO}(i,j)$ = Trunc(IDCT($Y_{(m,n)}^{WDCT}(i,j)$))+1, if the (i,j)$^{\text{th}}$ element of the translation map is 1

(2) $Y_{(m,n)}^{WHPSO}(i,j)$ = Trunc(IDCT($Y_{(m,n)}^{WDCT}(i,j)$)), if the (i,j)th element of the translation map is 0

Trunc function returns the integer part of a real number of IDCT coefficients. HPSO uses a constraint function to improve the quality of the extracted watermark as given below:

$$C = \sum_{i=1}^{4} \left| watermark\_block_i^o - watermark\_block_i^e \right| = 0 \qquad (14)$$

Where: watermark_block^o and watermark_block^e are the embedded and the extracted watermark blocks respectively. The solution sets in HPSO for each block are evaluated using fitness function.

Various objective functions based on error performance criterion are used to evaluate the performance of the above algorithm. Each objective function is fundamentally the same except for the section of code that defines the specific error performance criterion being implemented to train the elements of translation map for correcting the round error problem. The Performance index is calculated over each block. Performance indices used are given by:

-Integral of Absolute Magnitude of the Error (IAE)

$$fitness_{IAE} = \sum_{i=1}^{8} \sum_{j=1}^{8} \left| watermarked\_block(i,j) - original\_image\_block(i,j) \right| \qquad (15)$$

-Integral of the Square of the Error (ISE)

$$fitness_{ISE} = \sum_{i=1}^{8} \sum_{j=1}^{8} (watermarked\_block(i,j) - original\_image\_block(i,j))^2 \qquad (16)$$

-Mean of the Square of the Error (MSE)

$$fitness_{MSE} = \frac{1}{8 \times 8} \sum_{i=1}^{8} \sum_{j=1}^{8} (watermarked\_block(i,j) - original\_image\_block(i,j))^2 \qquad (17)$$

The effectiveness of the proposed HPSO algorithm in comparison with the standard PSO algorithm is tested using the above three performance indices.

By this constrain function, the extracted watermark is exactly similar to the embedded watermark, and in addition the quality of the watermarked image is achieved.

6. SIMULATION RESULTS

To evaluate the performance of HPSO using Cauchy mutation and roulette wheel selection experiments have been carried out for improving the performance of fragile watermark by embedding the watermark of figure 3 into the block image in figure 1 using the above different indices. The fitness value is evaluated with running the program 30 runs, with maximum number of generations 100, and population size equals 30 using standard PSO, and HPSO . The performance comparison of standard PSO introduced in [22] and HPSO algorithm in terms of convergence speed for the rounding problem of embedding the watermark in figure 3 into the image in figure 1 is shown in figures 6, 7, and 8 respectively.

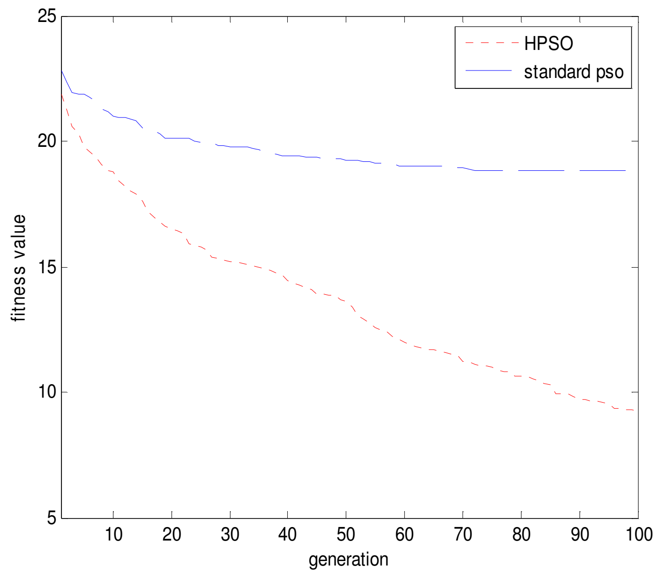

Figure 6. Average fitness value of the IAE fitness function using PSO and HPSO on the first example block with 30 runs

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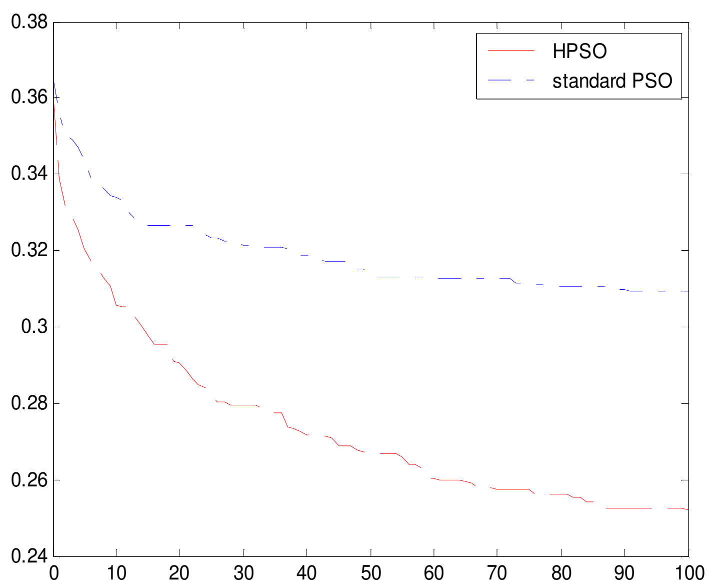


Figure 7. Average fitness value of the MSE fitness function using PSO and HPSO on the first example block with 30 runs

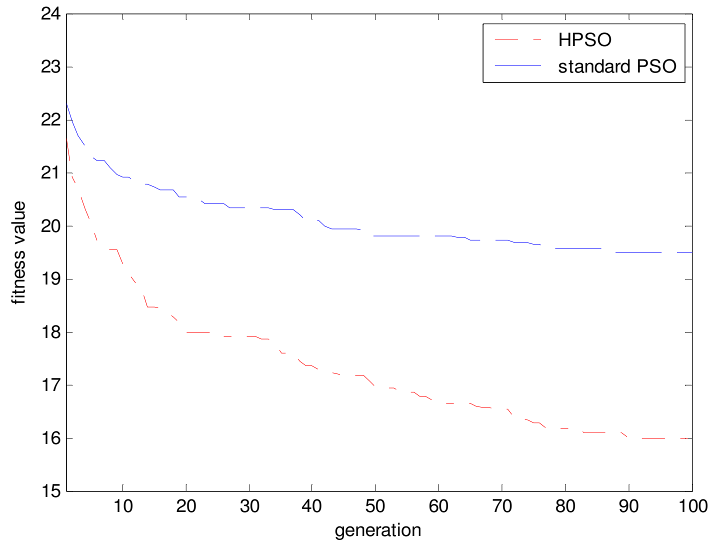


Figure 8. Average fitness value of the ISE fitness function using PSO and HPSO on the first example block with 30 runs

The average fitness values of the two algorithms across 30 runs using three indices show that HPSO is better than PSO alone. Besides, we demonstrate the efficiency of the proposed technique using IAE fitness function on three test images, Lena, F-16, and Peppers with size 256×256, and three binary watermark images rose, star, flag and of size 64×64. The images are shown in Figures 9 and 10 respectively.

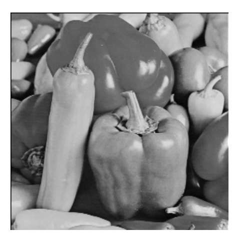


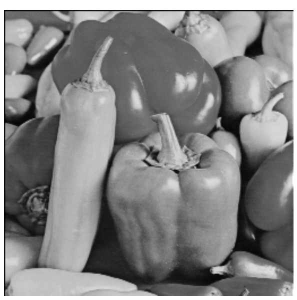
Figure 9: (a) Lena image (b) F-16 image (c) Peppers image

Figure 10: (a) rose watermark (b) star watermark (c) flag watermark

Figures 11-13 show the results of embedding the rose, star and flag watermark images into Lena, F-16 and Peppers host images. It is clear from the figures that the watermarked images are not distinguished from the original image.

Figure 11: (a) Lena image (b) Lena Watermarked image

Figure 12 (a) F-16 image (b) F-16 Watermarked image



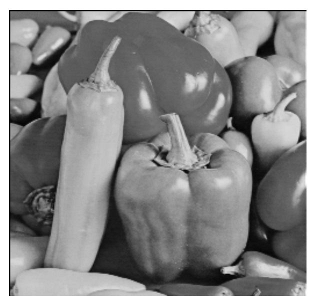


Figure 13: (a) Peppers image (b) Peppers Watermarked image

Figures 14-16 show the extracted Rose watermark from Lena image using simple rounding, standard PSO, and HPSO techniques after 20 iterations, and with population size equals 30. Also, Figures 17-19 are the extracted star watermark from F-16 image by using simple rounding, standard PSO, and the proposed HPSO watermarking method. Finally, figures 20-22 show the extracted Flag watermark from peppers image using simple rounding, standard PSO, and HPSO method.

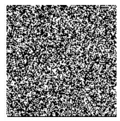


Figure14. Rose extracted using simple round Technique

Figure15. Rose extracted using PSO algorithm

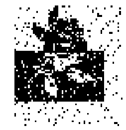


Figure16. Rose extracted using HPSO algorithm

Figure17. Star extracted using round technique

Figure18. Star extracted using PSO algorithm

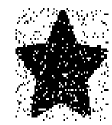


Figure19. Star extracted using HPSO algorithm

Figure20. Flag extracted using round technique

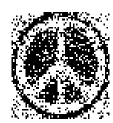


Figure21. Flag extracted using PSO algorithm

Figure22. Flag extracted using HPSO algorithm

As we shown from figures, the embedded watermarks are easily identified and can be detected and extracted from the host images after minimum number of iterations using HPSO comparing with the standard PSO and the simple rounding technique which could not detect the embedded watermark.
To determine the quality of watermarked image, MSE between the original and the watermarked image is calculated as:

$$MSE = \frac{1}{M \times N} \sum_{i=1}^{M} \sum_{j=1}^{N} \left[Y(i,j) - Y^{W}(i,j) \right]^2 \qquad (18)$$

The watermarked image quality is represented by the peak signal to noise ratio between the watermarked image Y^W and the host image Y and is formulated by:

$$PSNR = 10 \log_{10} \left(\frac{255^2}{MSE} \right) \quad (dB) \qquad (19)$$

The metric to measure the robustness is the normalized cross correlation (NC) between the embedded watermark W (i ,j) and the extracted ones W' (i ,j) which is defined as:

$$NC = \frac{\sum_{i=1}^{M_w}\sum_{j=1}^{N_w}\left[W(i,j)\times W'(i,j)\right]}{\sum_{i=1}^{M_w}\sum_{j=1}^{N_w}\left[W(i,j)\right]^2} \tag{20}$$

The values of PSNR, and NC using simple rounded, PSO, and HPSO after 20 iterations and with population size equals 30 are depicted in table 1.

Table 1: the values of NC, PSNR with simple rounded, PSO, and HPSO

Image	Simple rounding		Standard PSO		HPSO	
	NC	**PSNR**	**NC**	**PSNR**	**NC**	**PSNR**
Lena	0.475	61	0.8	50	0.9	53
F-16	0.48	62	0.8	51	0.9	54
Peppers	0.49	63	0.82	52	0.91	54

The experimental results prove the superiority of HPSO technique after 20 iterations and population size equals 30 over the simple rounding and PSO techniques in terms of PSNR and NC, and it has a convergence rate faster than PSO.

7. CONCLUSION

This paper is concerned with developing the standard PSO using mutation operator and evolutionary selection. A novel technique using PSO merging with Cauchy mutation and roulette wheel selection namely HPSO is proposed in this paper. Cauchy mutation is introduced for its long jump ability to escape from local minima, and roulette selection for its easy implementation to keep the best-performed particles in each generation. Besides the paper investigates the use of HPSO for solving the rounding error problem in fragile watermarking which results from the conversion of real numbers of the IDCT modified coefficients to integer numbers. The performance of HPSO and the standard PSO is analyzed with three different indices IAE, MSE, and ISE on test block image. In addition, the performance of the proposed algorithm is compared with the simple rounding technique, and the standard PSO on Lena, F16, and Peppers test images. The experimental results using the three different host images and watermarks images show the superiority of HPSO over the standard PSO and simple rounded process in terms of PSNR and NC. NC is always close to 1 in HPSO comparing with the standard PSO, and the simple rounding technique after 20 iterations. Also, it has been shown that the developed algorithm is faster in convergence and gives higher fitness comparing with the standard PSO. In the future research we intend to apply the proposed technique to the robust image watermarking to prove its efficiency under several image attacks.

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