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ORIGINAL ARTICLE

An adaptive watermarking approach based on weighted quantum particle swarm optimization

Mona M. Soliman · Aboul Ella Hassanien · Hoda M. Onsi

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Abstract In this paper, we propose a novel optimal singular value decomposition (SVD)-based image watermarking approach that uses a new combination of weighted quantum particle swarm optimization (WQPSO) algorithm and a human visual system (HVS) model for both the hybrid discrete wavelet transform and discrete cosine transform (DCT). The proposed SVD-based watermarking approach initially decomposes the host image into subbands; afterwards, singular values of the DCT of the lower sub-band of the host image are quantized using a set of optimal quantization steps deduced from a combination of the WQPSO algorithm and the HVS model. To evaluate the performance of the proposed approach, we present tests on different images. The experimental results show that the proposed approach yields a watermarked image with good visual definition; at the same time, the embedded watermark was robust against a wide variety of common attacks, including JPEG compression, Gaussian noise, salt and pepper noises, Gaussian filters, median filters, image cropping, and image scaling. Moreover, the results of various experimental analyses demonstrated the superiority of the WQPSO approach over other optimization techniques, including classical PSO and QPSO in terms of local convergence speed, resulting in a better balance between global and local searches of the watermarking algorithm.

Keywords Quantum-behaved particle swarm optimization · Watermarking · Singular value decomposition · Optimization

M. M. Soliman · A. E. Hassanien (✉) · H. M. Onsi
Faculty of Computers and Information, Cairo University, 5 Ahamed Zewal Street, Orman, Giza, Egypt
e-mail: aboitcairo@gmail.com; abo@egyptscience.net
URL: http://www.egyptscience.net

M. M. Soliman
e-mail: mona.solyman@fci-cu.edu.eg

H. M. Onsi
e-mail: h.onsi@fci-cu.edu.eg

M. M. Soliman · A. E. Hassanien
Scientific Research Group in Egypt (SRGE), Giza, Egypt

1 Introduction

Quantum mechanics is the theory that explains and predicts the behaviour of particles such as electrons, protons, neutrons, atomic nuclei, atoms and molecules, as well as photons. From quantum theory, we obtain the laws of chemistry as well as an explanation of the properties of materials, such as crystals, semiconductors, superconductors, and super-fluids. Applications of quantum behaviour include transistors, computer chips, lasers, and masers [1]. Quantum computing is a new class that investigates the computational power and other properties of computers based on quantum mechanical principles. This research area was first proposed by Benioff in the early 1980s [2]. An important objective is to find quantum algorithms that are significantly faster than any classical algorithm solving the same problem [3]. Since Benioff introduces quantum computing, it has been developed rapidly, and it also has been turning out that quantum computing has significant potential to be applied to various difficult problems including optimization.

Particle swarm optimization (PSO) is a relatively simple optimization technique, and it is easier to be understood compared with some other evolutionary computation methods. It is widely used in different fields including watermarking technologies [4–9]. However, the global convergence of PSO cannot always be guaranteed because the diversity of population is decreased with evolution developed [10]. To deal with this problem, concept of a global convergence guaranteed method called as quantum-behaved particle swarm optimization (QPSO) was developed [11]. The iterative equation of QPSO is very different from that of PSO. QPSO strategy as proposed by Sun in [11] is based on a quantum potential well model to sample around the previous best points. QPSO provides a good scheme for improving classical PSO on several aspects, such as simple evolution equations, more few control parameters, fast convergence speed, and simple operation. QPSO is considered theoretically a global convergence algorithm [10]. The QPSO algorithm has been shown to successfully solve a wide range of continuous optimization problems, and many efficient strategies have been proposed to improve the algorithm [12–15]. Weighted QPSO (WQPSO) is introduced in [16] as an improved quantum-behaved PSO algorithm. In order to balance the global and local searching abilities, a weight parameter in calculating the mean best position in QPSO is introduced. Such weighting parameter is used to render the importance of particles in population when they are evolving. So, the particle swarm does never abandon any lagged particle [17]. Each particle cannot converge to global best position without considering its neighbours, thus considered to be more intelligent and more cooperative social organism.

Digital watermarking is actually derive from steganography, a process in which digital content is hide with the other content for safe transmission of digital data. In particular, process of steganography and watermarking is very similar [18]. The main difference between these two processes is in steganography, the hidden data are on highest priority for sender and receiver but in watermarking, both hidden data and digital media are on highest priority. The hidden information to be embedded can be some text, author's serial number, company logo, and images with some special importance. Digital watermarking is being used in broadcast and Internet monitoring, forensic tracking, copy protection, counterfeit deterrence, authentication, copyright communication, and e-commerce applications. It is now also being adopted for use in US drivers licences to enable applications that require cross-jurisdictional authentication and forensic analysis [19]. There are many different proposed algorithms for watermarking. Each type of these algorithms has its own advantages and limitations. Watermarking techniques can be categorized in different ways [20]. The watermark can be classified according to its visibility. There are two types of watermarks: the visible ones, like different logos either on paper or on a TV screen, and, the most important one, the invisible watermarks, which cannot be detected by the human visual system. An invisible watermark can be classified into robust, semi-fragile, and fragile watermark. The watermark can be classified based on the level of required information at extraction process into blind watermarks, semi-blind watermarks, and non-blind watermarks. Watermark can also be classified according to watermarking embedding techniques. Watermark can be embedded either in spatial or frequency domain [21]. Both the domains are different and have their own pros and cons and are used in different scenario.

The theory of singular value decomposition (SVD) was investigated for real square matrices in the 1870s by Beltrami and Jordan and for complex matrices by Autonne in 1902 and has been extended to rectangular matrices by Eckart and Young in the 1939 [22]. Singular value decomposition (SVD) is one of the most powerful numeric analysis techniques with numerous applications including watermarking; therefore, many watermarking schemes that combine different transforms with SVD have been proposed lately [23–26]. The basic idea behind SVD-based watermarking approaches is to modify the singular values of the cover image by embedding watermark. There are three benefits to employ SVD method in digital image watermarking [27]: (1) the size of the matrices from SVD transformation is not fixed; (2) the singular values of an image have very good stability, that is, when a small perturbation is added to an image, its singular values do not change significantly; and (3) SVs represent intrinsic algebraic image properties. In general, the watermark can be scaled by a scaling factor SF which is used to control the strength of the watermark. The performance of the watermarking process highly depends on choosing a proper scaling factor [28]. The smaller the SF, the better the image quality and the weaker the robustness. However, the larger the SF, the more the distortion of the quality of the host image and the stronger the robustness [29]. Recently, many researchers focus on adaptive determination of the quantization parameters for SVD-based watermarking. They consider solving this problem using adopting artificial intelligence techniques or analysing statistical model of each block in the image [29–31].

In this paper, a novel SVD watermarking approach based on weighted quantum particle swarm optimization (WQPSO) is presented in order to balance the global and local searching abilities, focusing on adaptive determination of the quantization parameters for SVD. Two quantization parameters are used: one quantization parameter is determined by exploiting the characteristics of human visual system (HVS) [32] and the other quantization parameter is optimized through WQPSO algorithm. These two quantization parameters that are combined to ensure the final adaptive quantization steps are optimal for all embedding blocks. Such optimization of quantization step leads to a balance between the imperceptibility and robustness of the digital watermarking system.

The rest of this paper is organized as follows. In Sect. 2, some useful and important preliminary ideas are discussed. Related work of SVD-based watermarking schemes is explored in Sect. 3; then, the proposed algorithm is introduced in Sect. 4. Finally, simulation results are presented in Sect. 5 followed by conclusion and future work in Sect. 6.

2 Preliminaries

This section recalls some preliminaries of quantum PSO and weighted quantum PSO that are relevant to this paper.

2.1 Quantum particle swarm optimization

In terms of classical mechanics, a particle i with d dimension is represented with a position vector $X_i = (X_{i,1}, X_{i,2}, \ldots, X_{i,d})$ and a velocity vector $v_i = (v_{i,1}, v_{i,2}, \ldots, v_{i,d})$. In every time step t, particle i changes its velocity and position according to Eqs. (1) and (4).

$$v_{i,j}(t+1) = wv_{i,j}(t) + T1 + T2 \tag{1}$$

where

$$T1 = c_1 r_{1,i}(P_{i,j} - X_{i,j}(t)) \tag{2}$$

$$T2 = c_2 r_{2,i}(P_{g,j} - X_{i,j}(t)) \tag{3}$$

$$X_{i,j}(t+1) = X_{i,j}(t) + v_{i,j}(t+1). \tag{4}$$

where w is the inertial weight, c_1 and c_2 are normally set in range [0, 2] representing positive acceleration coefficients used to scale the contribution of cognitive and social components, respectively. r_1 and r_2 are uniform random variables in range [0, 1]. P_i is the best personal position of particle i which has been visited during the lifetime of the particle. P_g is the global best position that is the best position of all particles in the swarm.

The particle in classical PSO moves along a determined trajectory in Newtonian mechanics, but this is not the case in quantum mechanics. In quantum world, the term trajectory is meaningless, because x_i and v_i of a particle cannot be determined simultaneously according to the uncertainty principle. Therefore, if individual particles in a PSO system have quantum behaviour, the PSO algorithm is bound to work in a different fashion like the work introduced in [33].

Trajectory analysis demonstrated that to guarantee convergence of PSO algorithm, each particle must converge to its local attractor $P_i = (P_{i,1}, p_{i,2}, \ldots, P_{i,d})$ of which the coordinates are defined using Eq. (5) as described in [16]:

$$P_{i,j}(t) = \frac{c_1}{P_{i,j}}(t) + c_2 P_{g,j}(t) c_1 + c_2 \tag{5}$$

or

$$P_{i,j}(t) = Q \cdot P_{i,j}(t) + (1-Q) \cdot P_{g,j}(t), Q \sim (0,1) \tag{6}$$

where $j = 1, 2, \ldots, d, Q = c_1 r_1/(c_1 r_1 + c_2 r_2)$. It can be seen that the local attractor is a stochastic attractor of particle i that lies in a hyper-rectangle with P_i and P_g being two ends of its diagonal. Xi et al. [16] define the concepts of QPSO as follows. Assume that each individual particle move in the search space with a δ potential on each dimension, of which the centre is the point P_{ij}. For simplicity, we consider a particle in one-dimensional space, with point p the centre of potential. Solving Schrodinger equation [34] of a one-dimensional δ potential well, we can get the probability density function Q and distribution function F using Eqs. (7) and (8):

$$Q(X_{i,j}(t+1)) = \frac{1}{L_{i,j}(t)} \exp^{-2|P_{i,j}(t) - X_{i,j}(t+1)|/L_{i,j}(t)} \tag{7}$$

$$F(X_{i,j}(t+1)) = 1 - \exp^{-2|P_{i,j}(t) - X_{i,j}(t+1)|/L_{i,j}(t)} \tag{8}$$

where $L_{i,j}$ is the standard deviation of the distribution, which determines the search scope of each particle. Employing Monte Carlo method [35], we can obtain the jth component of position X_i at iteration $t+1$ using Eq. (9):

$$X_{i,j}(t+1) = P_{i,j}(t) \pm (L_{i,j}(t)/2) \ln(1/u_{i,j}(t+1)) \tag{9}$$

where $u_{i,j}(t+1)$ is a random number uniformly distributed in (0, 1). To evaluate $L_{i,j}(t)$, a global point called *Mainstream Thought* or *mean best* position of the population is introduced into classical PSO. The global point, denoted as $m(t)$, is defined as the mean of the *pbest* positions of all particles. That is, *mbest* can be calculated using Eq. (10):

$$m(t) = (m_1(t), \ldots, m_d(t)) \\ = \left[\frac{1}{M}\sum_{i=1}^{M} P_{i,1}(t), \frac{1}{M}\sum_{i=1}^{M} P_{i,2}(t), \ldots, \frac{1}{M}\sum_{i=1}^{M} P_{i,j}(t), \ldots, \frac{1}{M}\sum_{i=1}^{M} P_{i,d}(t)\right] \tag{10}$$

where M is population size and $P_i(t)$ is the best position of particle i. The value of $L_{i,j}(t)$ is determined by Eq. (11):

$$L_{i,j}(t) = 2\beta |m_j(t) - X_{i,j}(t)| \tag{11}$$

The parameter β is called contraction–expansion coefficient, which can be adjusted to balance the local search and the global search of the algorithm during the optimization process.

The quantum PSO algorithm starts with the initialization of the particles current positions and their *pbest* position, followed by iteration of updating the particle swarm. At each iteration, the *mbest* position of the particle swarm is computed and the current position of each particle is updated. Before each particle updates its current position, its fitness value is evaluated and then its *pbest* position and the *gbest* position are updated.

2.2 Weighted quantum particle swarm optimization

From Eq. (10), we can see that the *mbest* is simply the average on the personal best position of all particles, which means that each particle is considered equal and exerts the same influence on the value of *mbest*. The equally weighted mean position, however, is something of paradox, compared with the evolution of social culture in real world. For one thing, although the whole social organism determines the Mainstream Thought, it is not proper to consider each member equal. In fact, the elitists play more important role in culture development. With this in mind, a new control method for the QPSO is proposed in [16], where *mbest* in Eq. (10) is replaced for a weighted mean best position. The most important problem is how to evaluate particle importance in calculating the value of *mbest*. Based on this, we associate elitism with the particles' fitness value.

Describing it formally, we can rank the particle in descendent order according to their fitness value first then assign each particle a weight coefficient α_i linearly decreasing with the particle's rank, that is, the nearer the best solution, the larger its weight coefficient. The mean best position *mbest* is calculated using Eq. (12):

$$\begin{aligned} m(t) &= (m_1(t), \ldots, m_d(t)) \\ &= \left[\frac{1}{M}\sum_{i=1}^{M}\alpha_{i,1}P_{i,1}(t), \frac{1}{M}\sum_{i=1}^{M}\alpha_{i,2}P_{i,2}(t), \ldots, \frac{1}{M}\sum_{i=1}^{M}\alpha_{i,d}P_{i,d}(t)\right] \end{aligned} \tag{12}$$

where α_i is the weight coefficient, $\alpha_{i,j}$ is the dimension coefficient of every particle, and M is the population size

3 Related work

A SVD is a mathematical technique used to extract algebraic features from an image [36]. The main idea behind SVD-based approaches is to apply the SVD to the whole cover image or, alternatively, to small blocks of it and then modify the singular values to embed the watermark [37]. In general, the strength of the embedded watermark can be controlled by a scaling factor. The performance of the watermarking process highly depends on choosing a proper scaling factor [22]. However, determining the proper values of multiple scaling factors is a difficult problem, especially for different types of cover and watermark images. Different works had been introduced in order to improve the performance of SVD-based watermarking approaches by utilizing different methods in choosing the proper SF [38]. Some works depend on some general assumption in choosing the proper values of SF [27, 39]. Other works propose a systematic mechanism in choosing the proper values for SF [23, 40]. Recently, some works [28–30, 41] utilize intelligent optimization methods in modifying the SF in an intelligent adaptive way. It has been shown that by applying optimization techniques, such as genetic algorithm (GA) and PSO, into the watermarking algorithm, better outcomes in terms of both robustness and the imperceptibility can be obtained according to the properly designed fitness functions. This section explores some SVD-based watermarking approaches proposed in the past years.

Starting work of using SVD in watermark embedding is proposed based on assuming some general assumption in choosing the proper values of SF. In [27], the cover image decomposes into four sub-bands by one-level DWT. Then by applying SVD only to the intermediate frequency sub-bands, the watermark is embedded into the singular values of the aforementioned sub-bands. In this proposed work, Lai et el. use constant scaling factor (SF) in all experiments. The values of the scale factors are of constant range from 0.01 to 0.09 with an interval of 0.02. Khan et al. [39] described a digital image watermarking algorithm using discrete wavelet transform (DWT), discrete cosine transform (DCT), and SVD. In this work, the cover image is decomposed into sub-bands using DWT, and the DCT is applied on the first band only. The DCT is mapped into four quadrants using zigzag order. A constant SF is used to modify SVs of each quadrant. Ganic et al. [23] introduce more intelligent in choosing SF by using a systematic mechanism in choosing the proper values for SF. The watermark has been embedded to the original image in two layers. In the first layer, the cover image is divided into sub-blocks and then SVs of the watermark image is scaled by an adaptive scaling factor and distributed over the image blocks. In the second layer, all SVs of the image are scaled by using a constant scaling factor 0.1 and combined with the SVs of the watermarked image; then, the resultant values are substituted with the original image SVs. Recently, [40] proposed a watermark scheme with circulation, based on non-overlapping DWT and SVD. The basic idea is to divide the original host image and watermark image into non-overlapping blocks, respectively, and to the former DWT and SVD is applied. Second, the scrambling watermark by Chebyshev chaotic map is embedded into the singular value matrix of original components with circulation. The complete watermark information can be completely retrieved by extracting any consecutive four rows and columns from the blocked watermarked image.

Recently, much works on SVD watermarking paid attention to using intelligent optimization methods such as genetic algorithm (GA) and PSO in improving SVD-based watermarking approaches. For GA-SVD-based watermarking approaches, Aslantas in [29] proposes an optimal watermarking scheme based on SVD for grey-scale images by employing multiple SFs. Modifications are optimized using GA to obtain the highest possible robustness without losing the transparency. GA is utilized to search for optimal parameters in order to achieve the optimal performance of a digital image watermarking algorithm. In this work, the parameters to be optimized are the SFs. Lai [28] proposed an innovative image watermarking scheme by integrating SVD technique and the tiny genetic algorithm (Tiny-GA). The Tiny-GA offers a systematic way to consider the improvements in the scaling factors that are used to control the strength of the embedded watermark. Loukhaoukha [22] argue this method and stated that [28] does not guarantee an objective detection outcome and has a very high probability of a false-positive detection of the watermarks. Loukhaoukha et al. [22] proved such limitation of Loukhaoukha [28] by performing experiments on four different images. Lai et al. [30] proposed a novel image watermarking scheme by integrating SVD and micro-genetic algorithm (micro-GA). The proposed approach starts by estimating SVD directly from a cover image. The watermark is embedded by modifying SV using a scaling factor. The proper scaling factors are efficiently determined by micro-GA. The micro-GA is a real GA which evolves with a very small population.

PSO had been combined with SVD watermarking methods as in [8, 9, 41, 42]. The work in [41] proposed a watermarking algorithm that initially decomposes the host image into sub-bands using DWT; afterwards, singular values of each sub-band of the host image are modified with the scaling factors to embed watermark. Modifications are optimized using PSO to obtain the highest possible robustness without losing the transparency. Soliman et al. [8] design an adaptive watermarking scheme in medical imaging based on swarm intelligence. The watermark bits are embedded on singular value vector of each embedding block within low-frequency sub-band in the hybrid DWT–DCT domain. One quantization parameter is determined by exploiting the characteristics of HVS, and the other quantization parameter is optimized through PSO algorithm. Loukhaoukha et al. [42] proposed an optimal image watermarking scheme using multi-objective particle swarm optimization (MOPSO) and SVD in wavelet domain. The singular values of the specific sub-band are modified by multiple scaling factors (MSF) to embed the singular values of watermark image. The work in [42] utilizes the PSO to obtain optimum multiple scaling factors. Soliman et al. [9] provide an enhancement on the work in [8] where QPSO is used instead of classical PSO to optimize SVD-based watermark parameters. Both SVD-PSO and SVD-QPSO watermarking approaches are used to watermark medical image for sake of protecting patients privacy.

4 The proposed adaptive watermarking approach

The trade-off between the imperceptibility and robustness is one of the most challenges in digital watermarking system. Such trade-off problems can be solved by using optimization methods. This proposed work aims to provide a solution for such problem by using one of the bio-inspired optimization techniques PSO. A digital image watermarking optimization in the discrete wavelet domain is presented. The proposed watermarking approach is designed in such a way that it achieves the imperceptibility and robustness requirements by invoking weighted quantum particle swarm optimization (WQPSO) technique in adaptive quantization index modulation and SVD in conjunction with DWT and discrete cosine transform (DCT). The proposed watermarking approach consists of two procedures: watermarking embedding procedure and watermark extraction procedure. Both procedures are illustrated in detail in the following subsections.

4.1 Watermark embedding procedure

The watermark can be embedded into the host image through three consecutive phases. These phases are transformation, quantization, and embedding process. Figure 1 shows the architecture of the proposed watermark embedding procedure.

4.1.1 Transformation phase

The host image I_0 with $m \times n$ is transformed into the wavelet domain using discrete wavelet transform (DWT); three-level wavelet with filters of length four is used. We perform the L_th level discrete wavelet decomposition of the host image to produce a sequence of low-frequency sub-band *LL* and three high-frequency sub-bands *HL*, *LH*, and *HH*, corresponding to the horizontal, vertical, and diagonal details at each of the *L* resolution levels and a gross approximation of the image at the coarsest resolution level. By taking the advantage of low frequency coefficients which have a higher energy value and robustness against various signal processing, we segment the *LL* sub-band into non-overlapping blocks A_i with size $w \times w$. Then, we perform the discrete cosine transform (DCT) on the low frequency coefficient *LL* for each block, followed by computation of the singular values vector of each frequency coefficient block A_i by SVD according to Eq. 13.

$$\mathrm{SVD}(A_i) = U_i S_i V_i^T \tag{13}$$

where U is an $w \times w$ real or complex unitary matrix, $S_i = (\sigma_{i1}, \sigma_{i2}, \ldots, \sigma_{iw})$ denotes a vector formed by the singular values of the frequency coefficient block A_i, and V^T (the conjugate transpose of V) is an $w \times w$ real or complex

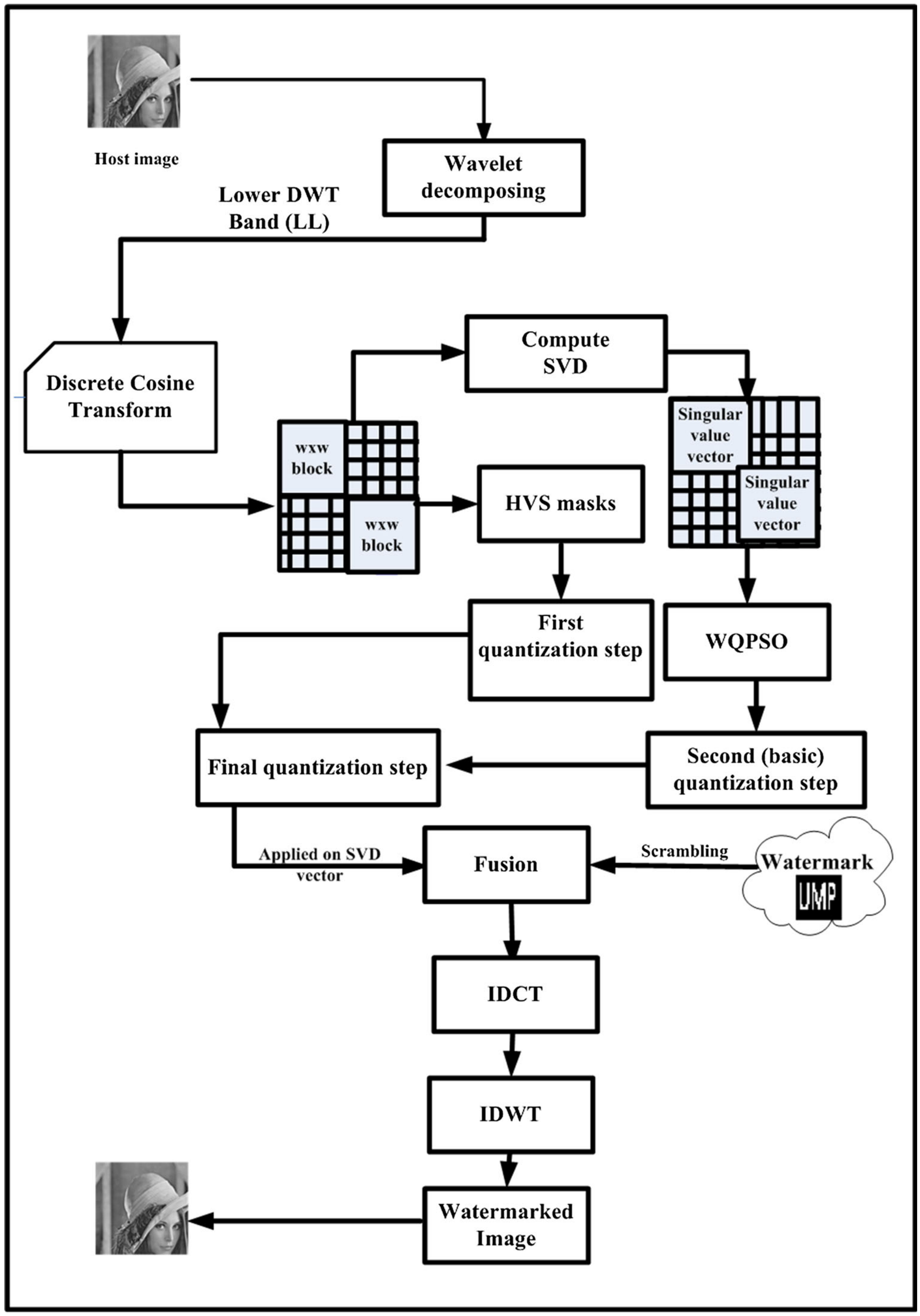


Fig. 1 Embedding procedure

unitary matrix. The w columns of U and the w columns of V are called the left-singular vectors and right-singular vectors of $\mathrm{SVD}(A_i)$, respectively.

The N_i^s is then computed that represents each block by one value, and each block is quantized to a proper quantization step δ_i according to Eqs. 14 and 15.

$$N_i^s = \|s_i\| + 1 \quad (14)$$

$$N_i = \left\lfloor \frac{N_i^s}{\delta_i} \right\rfloor \quad i = 1, 2, \ldots M \quad (15)$$

4.1.2 *Quantization phase*

A set of final quantization steps are modelled both the characteristics of the DCT domain HVS and weighted quantum PSO of each block to ensure a high perceptual quality of watermarked image and a low bit error rate of the detected watermark. This final quantization step is determined as a combination of two quantization steps: one comes from human visual system (HVS) by using luminance mask M_i^L and texture mask M_i^T and the other quantization step is determined by using WQPSO training. When WQPSO algorithm converge, it gives a basic quantization step δ_{i0} used to formulate the final quantization step δ_i using Eq. 16.

$$\delta_i = \left\lfloor \left(log2^{M_i^L M_i^T} \right)(1000) \right\rfloor / 1000 + \delta_{i0} \tag{16}$$

The basic quantization step developed by weighted quantum PSO algorithm is estimated by iteratively adding watermark sequence on tested images with different attack parameters. In each iteration, a fitness function value that combines both impressibility parameter and robustness parameter is evaluated. Based on best fitness function value, a basic quantization step is calculated for each block. In order to measure the fitness of each particle in each iteration, we have to select a fitness function that reflects both the imperceptibility and robustness. We adopt the same fitness function used in [8]:

$$f_i = \left\lfloor \frac{m}{\sum_{i=1}^{m} NC_i(w_i', w)} - NC(I_0', I_0) \right\rfloor^{-1} \tag{17}$$

where $NC(I_0', I_0)$ denotes 2D normalized correlation between original and watermarked image, $NC_i(w_i', w)$ denotes 2D normalized correlation between original and extracted watermark, and m represents number of attacking methods.

4.1.3 Watermark embedding phase

The watermark in this work is scrambled first in order to improve watermark robustness. Image scrambling is to use some algorithm to scramble every pixel in an image, but the sum of pixels is invariable. Image scrambling technology depends on data hiding technology which provides non-password security algorithm for information hiding [43]. After the watermark is processed by scrambling algorithm, even if an attacker detects the watermark, he cannot recover the original watermark without the knowledge of scrambling algorithm [44]. In this work, Arnold transform [43] is chosen as scrambling mechanism on original watermark as it is simple and periodic. The modified watermark is embedded into the singular values vector of each block by adaptive and optimized quantization steps according to Eq. 18.

$$N_{iw} = \begin{cases} N_i + 1, & \text{if } (mod(N,2), W_i) = (1,1) \text{ } or \text{ } (0,0) \\ N_i, & \text{otherwise} \end{cases} \tag{18}$$

Now we have to compute the modified singular value that will hold watermark information.

$$(\sigma_{i1}, \sigma_{i2}, \ldots, \sigma_{iw}) = (\sigma_{i1}, \sigma_{i2}, \ldots, \sigma_{iw}) \times \left(\frac{N_{iw}^s}{N_i^s} \right) \tag{19}$$

where $N_{iw}^s = \sigma_i \times N_{iw} + 0.5$.

Finally, the watermarked block A_i' is computed with modified singular values. The watermarked low-frequency sub-band LL is reshaped through A_i' by using inverse discrete cosine transform (IDCT); then, the watermarked image I_0' is obtained utilizing inverse discrete wavelet transform (IDWT).

4.2 Watermark extraction procedure

The watermark extracting procedure goes through the same steps of the embedding algorithm except that now we have an optimal final quantization step δ_{final_i} which is derived during the embedding procedure. Figure 2 shows in detail the extraction procedure.

Watermark bits are extracted according to the following equation:

$$W_i' = \begin{cases} 1, & \text{if} \quad mod(N_i', 2) = 0; \\ 0, & \text{else} \quad mod(N_i', 2) = 1. \end{cases} \tag{20}$$

where

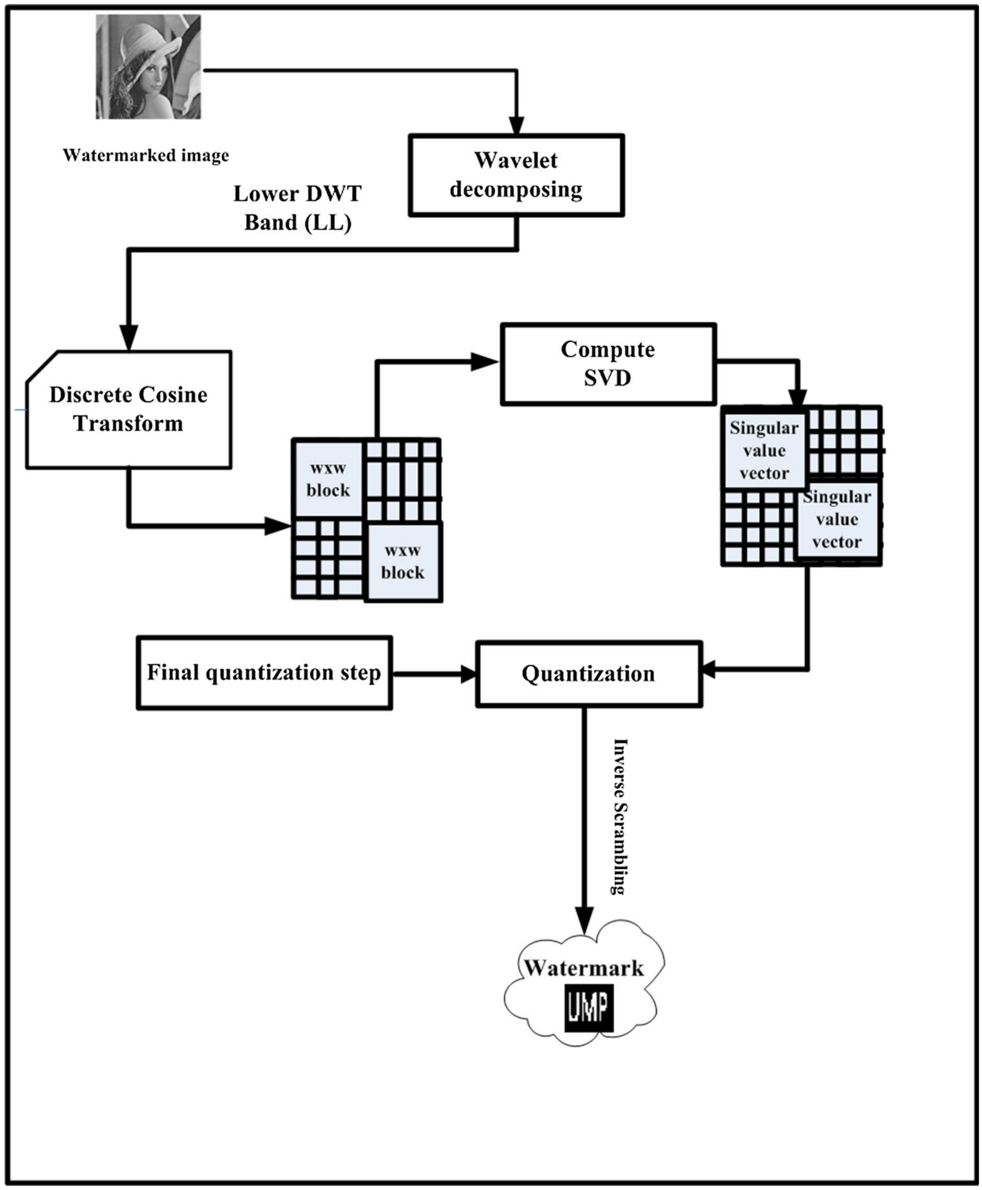
$$N_i' = \left\lfloor \frac{N_i^s}{\delta_{\text{final}_i}} \right\rfloor i = 1, 2, \ldots, M \tag{21}$$

5 Experimental results and analysis

In order to resist the normal signal processing and other different attacks, we wish the quantization step to be as high as possible. However, because the watermark directly affects the host image, it is obvious that the higher the quantization step, the lower the quality of the watermarked image will be. In other words, the robustness and the imperceptibility of the watermark are contradictory to each other. The imperceptibility means a measure that the perceptual difference between the cover and watermarked images should be undistinguished by the human visual inspection [4]. On the other hand, the robustness means a measure that an embedded watermark can be extractable even if common signal processing operations are applied to the watermarked image [5].

We use the peak signal-to-noise ratio (PSNR) as an efficient measure of visual fidelity between the host image and the watermarked image. This gives us an indication of the imperceptibility factor. To investigate the robustness of watermark schemes, each watermarked image is attacked

Fig. 2 Extraction procedure



using different image-processing attacks. The watermarking approach should be robust to signal processing attacks. Normalized correlation (NC) is used for evaluating the robustness of the watermarking approach.

The results of various experimental analysis of proposed watermark approach using WQPSO are compared with other optimization techniques including classical PSO [8] and quantum PSO [9], all in terms of PSNR and NC values.

In all the experiments, different parameters are required to be initialized first in order to start training procedure of PSO, QPSO, and WQPSO. The swarm population is set to be 20 swarm. The number of generations is 50 generation. For PSO [8], the self-recognition component $c_1 = 1.2$, the social component $c_2 = 1.8$, and the inertial weight w is linearly decreasing from 0.9 to 0.4. For QPSO [9], the contraction–expansion coefficient β is linearly decreasing from 0.5 to 0.1. For this proposed WQPSO approach, β coefficient is also linearly decreasing from 0.5 to 0.1, while α_i coefficient is linearly decreasing from 1.5 to 0.5.

We test our proposed watermarking approach on three images such as Lena, Peppers, and Gold-hill images, and the watermark of length 32×32 is embedded in those tested images.

5.1 Baseline evaluation

The result of embedding procedure on tested images is shown in Fig. 3. It shows the original and three watermarked images using PSO, QPSO, and WQPSO, respectively. One can simply see that the watermarked images have good visual fidelity. It is hard to distinguish visually between original image and watermarked image.

Fig. 3 From *left* to *right*: host image, watermarked image using PSO, QPSO, WQPSO, respectively

Table 1 PSNR values for ordinary images with PSO, QPSO, and WQPSO

Image	PSO [8]	QPSO [9]	WQPSO
Lena	54.34	55.95	55.03
Peppers	54.95	55.32	55.63
Gold-hill	54.39	54.87	55.21

The PSNR values used for quality comparison between the original and the watermarked images are shown in Table 1. It can be seen that PSNR values in case of WQPSO is higher than PSNR for both QPSO and classical PSO which means that the visual fidelity of WQPSO is superior to the two other methods.

5.2 Robustness evaluation

To evaluate the robustness of the proposed method, the watermarked image was tested against five kinds of image-processing attacks as: (1) format-compression attack: JPEG compression with quality factors between 30 and 50 %; (2) noise attack: Gaussian noise with zero mean and standard deviation taking two values (0.001 and 0.005), and salt and pepper noise with density (0.001 and 0.005); (3) denoising attack: filtration noise by considering two types of filters, Gaussian filter with size (3×3 and 5×5) with standard deviation of 0.1 and median filter with size (3×3 and 5×5); (4) geometrical attack: scaling attack with 75 and 50 % ratios; and (5) the cropping attack. Here, the watermarked images are attacked by cropping 25 and 35 % of areas. The cropping operation is performed on the top left corner of each test image. Tables 2, 3, 4, 5, 6, 7, and 8 summarize the NC values resulted from applying the seven attacks described before—JPEG compression, Gaussian noise, salt and pepper, Gaussian filter, median filter, scaling, and cropping on set of tested images.

Table 2 Robustness against JPEG compression

Method	QF	Lena	Pepper	Gold-hill
PSO	50	0.974	0.980	0.982
QPSO		0.982	0.982	0.982
WQPSO		0.982	0.982	0.982
PSO	40	0.978	0.978	0.977
QPSO		0.982	0.982	0.982
WQPSO		0.982	0.982	0.982
PSO	30	0.964	0.962	0.975
QPSO		0.982	0.982	0.982
WQPSO		0.982	0.982	0.982

5.3 Convergence comparison

From Tables 2, 3, 4, 5, 6, 7, and 8, it is clear that the robustness performance of the watermarking approaches using QPSO and WQPSO as optimization procedure in estimating adaptive quantization step is superior.

Table 3 Robustness for Gaussian noise attacks

Var.	Alg.	Lena	Peppers	Gold-hill
0.001	PSO	0.966	0.973	0.973
0.005		0.885	0.783	0.867
0.001	QPSO	0.982	0.982	0.982
0.005		0.927	0.770	0.927
0.001	WQPSO	0.982	0.982	0.982
0.005		0.936	0.830	0.908

Table 4 Robustness for salt and pepper noise attacks

Density	Alg.	Lena	Peppers	Gold-hill
0.001	PSO	0.974	0.977	0.978
0.005		0.963	0.919	0.953
0.001	QPSO	0.982	0.982	0.982
0.005		0.982	0.954	0.982
0.001	WQPSO	0.982	0.982	0.982
0.005		0.982	0.936	0.982

Table 5 Robustness for Gaussian filter attacks

Size	Alg.	Lena	Peppers	Gold-hill
3 × 3	PSO	0.977	0.981	0.980
5 × 5		0.981	0.980	0.981
3 × 3	QPSO	0.982	0.982	0.982
5 × 5		0.982	0.982	0.982
3 × 3	WQPSO	0.982	0.982	0.982
5 × 5		0.982	0.982	0.982

Table 6 Robustness for median filter attacks

Size	Alg.	Lena	Peppers	Gold-hill
3 × 3	PSO	0.923	0.962	0.944
5 × 5		0.780	0.886	0.741
3 × 3	QPSO	0.907	0.973	0.982
5 × 5		0.771	0.889	0.740
3 × 3	WQPSO	0.917	0.982	0.964
5 × 5		0.761	0.898	0.744

Table 7 Robustness for scaling attacks

Ratio (%)	Alg.	Lena	Peppers	Gold-hill
75	PSO	0.977	0.978	0.980
50		0.976	0.973	0.978
75	QPSO	0.982	0.982	0.982
50		0.982	0.973	0.982
75	WQPSO	0.982	0.982	0.982
50		0.982	0.973	0.982

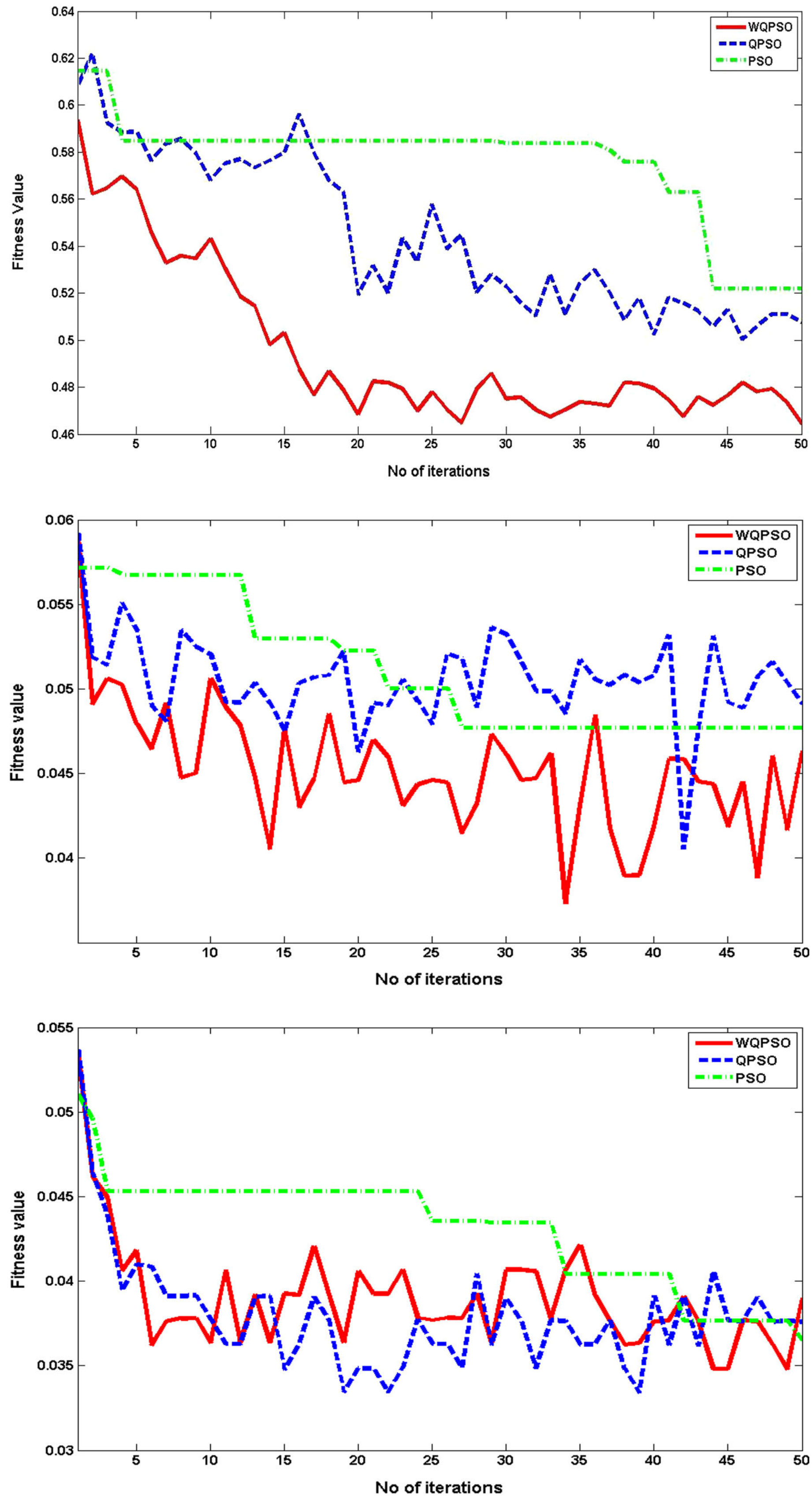
Table 8 Robustness for cropping attacks

Ratio (%)	Alg.	Lena	Peppers	Gold-hill
25	PSO	0.942	0.945	0.944
35		0.978	0.886	0.884
25	QPSO	0.946	0.946	0.946
35		0.871	0.919	0.910
25	WQPSO	0.946	0.946	0.946
35		0.861	0.901	0.871

Comparing the performances of WQPSO and QPSO for different values of noise parameters, we show that WQPSO provides higher *NC* values for most cases of the tested images, indicating that watermarking based on WQPSO is more robust. The explanation of such superior of both QPSO and WQPSO can be cleared by showing the convergence figures. Figure 4 gives the comparison of convergence processes of PSO, QPSO, and WQPSO for Lena, Pepper, and Gold-hill images, respectively, averaged over 50 trial runs; these samples are captured during assignment of different noise parameters shown in previous tables.

Although classical PSO converges to the global solution, it is not a global optimization technique, since it can get trapped in local minima as indicated by smooth variation of classical PSO curves in the convergence figures. Another common problem of classical PSO is its control parameters. Classical PSO has many control parameters. The convergence of the algorithm depends on the value of these control parameters. Tuning a proper value for convergence is a hard work. QPSO solve such a problem by introducing a new algorithm of PSO which depends only on one control parameter and in which the movement of particles is inspired by the quantum mechanics. This only control parameter is called contraction–expansion coefficient β, which can be adjusted to guarantee finding optimal solution in search space. In order to balance the global and local searching abilities, a weight parameter α is added in calculating the mean best position for QPSO to render the importance of particles in swarm population when they are evolving. Such weighting parameter convert QPSO algorithm into WQPSO algorithm. From convergence figures, we can show that WQPSO has the fastest convergence compared with PSO and QPSO. Since the parameter setting in WQPSO is the same as in QPSO, the fast convergence of WQPSO may be due to the weighted mean best position, which makes the particle converges to global best position more quickly.

Fig. 4 Comparison of convergence process for Lena, Pepper, Gold-hill images, respectively



6 Conclusion and future works

In this paper, we proposed the use of weighted quantum PSO algorithm (WQPSO) to determine the proper quantization step that was used to embed watermark bits into the singular values vector of each block of the host image. In the present watermarking approach, WQPSO introduced a linearly decreasing weight parameter to render the importance of particles in evolving populations. According to our proposed approach, the embedded watermark can successfully survive after attacked by image-processing operations. Simulation results show that the proposed approach outperforms the other similar works. Moreover, the results of various experimental analyses demonstrated the superiority of the WQPSO approach over other optimization techniques in terms of local convergence speed. Further work of extending the proposed approach will be devoted to find out an adaptive method to update weight coefficient α_i instead of updating it using linearly decreasing method. We believe that it will enhance the performance of WQPSO further.

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