Application of GA and PSO to the Analysis of Digital Image Watermarking Processes

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Abstract – The increasing effect of illegal exploitation and imitation of digital images in the field of image processing has led to the urgent development in the growth of copyright protection methods. Digital watermarking has proved best in protecting illegal authentication of data. In this paper, we propose a digital image watermarking scheme based on computational intelligence paradigms like Genetic Algorithm (GA) and Particle Swarm Optimization (PSO). The input digital host images undergo a set of pre-watermarking stages like image segmentation, feature extraction, orientation assignment, and image normalization to obtain image invariance properties when subject to attacks. Expectation Maximization (EM) algorithm is used to segment the images and the features are extracted using Difference of Gaussian (DoG) technique. The feature maps from the feature extraction methods locate the magnitude by orientation assignment making the circular regions invariant. The resultant image is normalized by scaling to acquire the scaling invariance for the circular region. The watermark image is then embedded into the host image using Discrete Wavelet Transform (DWT). During the extraction process, GA, and PSO are applied to improve the robustness, and fidelity of the watermarked image by evaluating the fitness function. The perceptual transparency and the robustness of the watermarked and the extracted images are evaluated by applying filtering attacks, additive noise, rotation, scaling and JPEG compression attacks to the watermarked image. From the simulation results the performance of the Particle Swarm Optimization technique is proved best based on the computed robustness and transparency measures along with the evaluated parameters like elapsed time, computation time and fitness value. The performance of proposed scheme was evaluated with a set of 50 textures images taken from online resources of Tampere University of Technology, Finland and the entire algorithm for different stages was simulated using MATLAB R2008b.

Keywords – Expectation Maximization, Difference of Gaussian, Orientation Assignment, Image Normalization, DWT, Genetic algorithm, Particle Swarm Optimization.

1. Introduction

Effective digital image copyright protection methods have become a vital and instantaneous necessitate in multimedia applications due to the increasing unauthorized manipulation and reproduction of original digital objects. Multimedia data protection has become one of the interesting challenge and has drawn the attention of researchers towards the development of protection approaches. Among several protection methodologies, digital watermarking is the leading approach, to protect illegal authentication of data [1]. Digital image watermarking is a technique to embed a secret message or valuable information (watermark) within an ordinary image (host image) and extract the image at the destination, therefore protecting the image from common image processing attacks during the transmission process. The watermark can either be a random signal, an organization's trademark symbol, or a copyright message for copy control and authentication. The chosen watermark to be embedded in the host image should be resilient to standard manipulations of unintentional as well as intentional nature, should be statistically unremovable, and must be capable of withstanding multiple watermarking to facilitate traitor tracing [2]. The type of manipulations and the signal processing attacks on the watermark depend upon the specific application of digital image watermarking. The most important characteristics of digital watermarking such as imperceptibility, robustness, inseparability, security, provable, permanence, data capacity, and fidelity allow the technique applicable in owner identification, copyright protection, image authentication, broadcast monitoring, transaction tracking, and usage control.

The frequently used watermarking techniques are spatial domain watermarking and frequency domain watermarking. Spatial domain was the first watermarking scheme, in which the perceptual information about the image was obtained and used to embed the watermarking key in the predefined intensity regions of the image. Embedding an invisible watermark was more simple and effective in the spatial domain, but when subject to image alterations the robustness was poor [1]. In the frequency domain, the watermark is transformed into the frequency domain by application of Fourier, discrete cosine or the discrete wavelet transforms. The watermarks are added to the transform coefficients of the image instead of modifying the pixels, thus making it difficult to remove the embedded watermark. Compared to spatial domain technique, frequency domain techniques are more robust and have a high range of control in maintaining the perceptual quality of the watermark. Discrete Wavelet Transform (DWT) is one of the most attractive transform domain watermarking techniques since it is a computationally efficient version of the frequency models for the human visual system [3]. DWT has exceptional properties like excellent localization in time and frequency domain, symmetric spread distributions and multiresolution characteristics [4] which led to the development of various DWT based algorithms.

In this paper, initially, the host image is segmented into a number of homogeneous regions using the Expectation Maximization (EM) algorithm and the feature points are extracted based on the difference of Gaussian (DoG) algorithm. Then the circular regions based on image normalization and orientation assignment are defined for

DWT based watermark embedding or extraction process. There has been a considerable amount of research proposals on the applications of Discrete Wavelets Transform in digital image watermarking systems by virtue of its excellent and exceptional properties mentioned above, but the scope of optimization in this area is tremendously less. An optimized DWT for digital image watermarking is capable of producing perceptual transparency and robustness among the watermarked and the extracted images. During the past few years, evolutionary intelligent algorithms such as genetic algorithm (GA) and particle swarm optimization (PSO) have shown good performances in optimization problems [5] [6]. Moreover watermark techniques based on these evolutionary intelligent algorithms seemed to improve security, robustness, and quality of the watermarked images [7]. We propose a technique based on the evolutionary optimizers to choose the best geometric positions for embedding and extracting thereby preserving the information in watermarked image and preventing the loss of data due to geometric attacks, filtering attacks and JPEG compression. From the simulation results the performance of the Particle Optimization technique is proved best based on the evaluated parameters like robustness, transparency, elapsed time, CPU time and fitness value. The similarity measures of the extracted watermark and the transparency is maintained in the proposed method.

1.1 Related work

Dong Zheng, Sha Wang, and Jiying Zhao [8] proposed the watermark embedded and extraction scheme using the RST Invariant Image Watermarking Algorithm with Mathematical Modeling and Analysis of the Watermarking Processes. The basic experimental idea is extracted from this paper. The mathematical relationship between fidelity and robustness is established in their work. Though the experimental results show the effectiveness and accuracy in watermarking, the attacked watermark was not optimized. David G. Lowe [9], proposed a method for extracting distinctive invariant features from images that can be used to perform reliable matching between different views of an object or scene. They also explained about the steps involved in difference of Gaussian algorithm and to detect the feature points from the image without any loss of information by mathematical calculations. Several approaches have been proposed in literature to prove that application of GA to DWM provides effective robustness.

Ali Al-Haj et al. [11] proposed a technique to obtain optimal DWT-based image watermarking only if watermarking has been applied at specific wavelet sub-bands with specific watermark amplification values. This approach concentrated only on a few attacks with fixed values. *Zhicheng Wei* et al [12] proposed an algorithm that yielded a watermark that is invisible to human eyes and robust to various image manipulation, and the results showed that only some specific positions were the best choices for embedding the watermark. The authors applied GA to train the frequency set for embedding the watermark and compared their approach with the Cox's method to prove robustness. The analysis of GA was restricted to JPEG compression attack in their proposed method. In [13], Jin Cong et al proposed a scheme that does not require the original image because the informations from the shape specific points of the original image were been memorized by the neural network. This scheme applies the shape specific points technique and features point matching method by genetic algorithm for resisting geometric attacks. Simulations have confirmed that their scheme has high fidelity and is highly robust against geometric attacks and signal processing operations such as additive noise and JPEG compression.

G. Boato [14] et al. proposed a new flexible and effective evaluation tool based on genetic algorithms to test the robustness of digital image watermarking techniques. Given a set of possible attacks, the method finds the best possible un-watermarked image in terms of Weighted Peak Signal to Noise Ratio (WPSNR). Chin-Shiuh Shieh [15] proposed an innovative watermarking scheme based on genetic algorithms (GA) in the transform domain considering the watermarked image quality. Zne-Jung Lee et al. [16] proposed a hybrid technique, where the parameters of perceptual lossless ratio (PLR) were determined for two complementary watermark modulations. Furthermore, a hybrid algorithm based on genetic algorithm (GA) and particle swarm optimization (PSO) is simultaneously performed to find the optimal values of PLR instead of heuristics. In this approach, GA's crossover and mutation are performed in parallel with particle velocity update of PSO, which sometimes tends to get locked in the local optima without reaching the best solution. Ziqiang Wang et al. [17] proposed a novel blind watermark extracting scheme using the Discrete Wavelet Transform (DWT) and Particle Swarm Optimization (PSO) algorithm. In his work, the experimental results show that the proposed watermarking scheme results in an almost invisible difference between the watermarked image and the original image, and is robust only to JPEG lossy compression.

Almost all the related work concentrated Digital watermarking based on JPEG attacks, and in very few papers additional attacks like rotation and scaling are dealt. The performance of DWT based watermarking can be evaluated best for robustness by applying different attacks with varying parameters. We propose the hybrid technique for embedding and extracting watermarks thus conserving the information in watermarked image and also avoiding the hacking of data due to geometric attacks, additive noise attacks, filtering attacks and JPEG compression.

The sections of the paper are organized as follows: Section 2 deals with the details and the scheme of the digital image watermarking approach including image segmentation, feature extraction, orientation assignment, image normalization and DWT based watermarking. The optimization techniques Genetic Algorithm, Particle Swarm Optimization, and Hybrid Particle Swarm Optimization, its operators and the procedure for DWM techniques are elaborated in Section 3. The experimental analysis and results are explained in Section 4 and Section 5 deals with the conclusion.

2. Digital Image Watermarking Scheme

The proposed watermarking scheme is illustrated in Figure 1. In the scheme, first, the image is segmented into a number of homogeneous regions by Expectation Maximization (EM) algorithm and by applying the DoG filter the feature points are extracted [8]. Based on image normalization and orientation assignment, the circular regions are chosen for watermark embedding and extraction. In this section, the phases of the watermarking scheme are discussed.

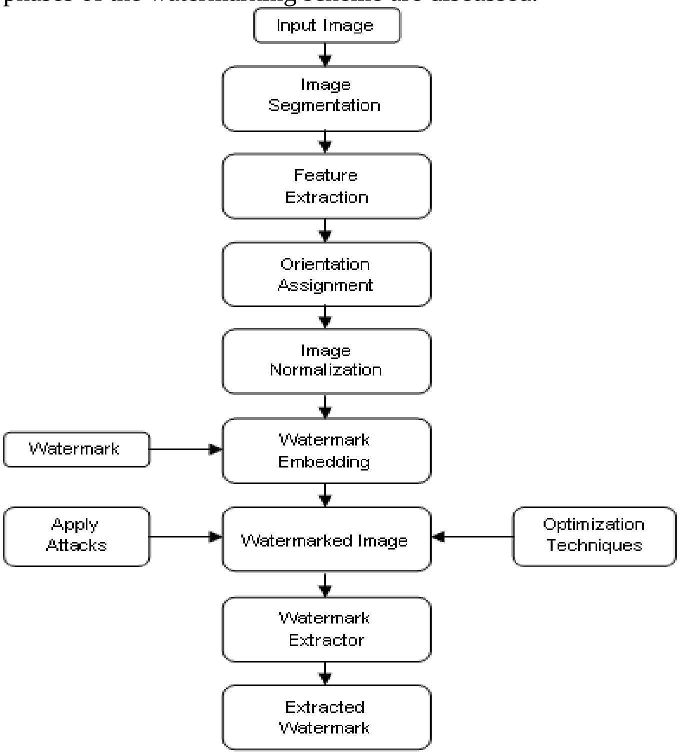


Figure 1 Watermark Embedding and Extraction Scheme

2.1 Image Segmentation

Image segmentation is an elegant technique in which a signal is decomposed into segments with different time and frequency resolutions. The goal of segmentation is to simplify and change the representation of an image interms of different homogeneous regions that is more meaningful and easier to analyze. Expectation-maximization algorithm is used for image segmentation and hence to determine the embedding strength of the segmented homogenous region. The mean vector and the covariance matrix of each homogeneous area is computed and this aids in implementing the watermark embedding process [18]. The EM is an iterative procedure alternating between an expectation (E) step and a maximization (M) step. The E step computes an expectation of the log likelihood with respect to the current estimate of the distribution for the latent variables. The M step computes the parameters which maximize the expected log likelihood found in the E step [19] [20]. These parameters are then used to determine the distribution of the latent variables in the next iterative E step. Assume the observed image is y and the segmentation region is x, for each subregion x_s, the conditional distribution of y_s (subregion of y) given x_s is a Gaussian distribution with mean and variance. The mixture Gaussian distribution is used to model the observed image y by eq. 1,

$$Py_s|x_s(y_s|x_s) \sim N(\mu y_s), \sigma y_s) \qquad (1)$$

Where, μy_s is the mean of the segmented image, σy_s is the variance of the segmented image and N is the number of segmented regions. The density is given as,

P_{yx} (y,x) = $\sum_{s\varepsilon S} m_s\, p_{ys\ xs}(\frac{y_s}{x_s})$,where m_s is the mixture weighting factor (2)

For each distribution, the mean vector and covariance are set to predefined initial values. The covariance can be set as the identity matrix and the mean is calculated by determining the average of different regions of the image. Then the probability of the pixel falling into one of the Gaussian distribution can be calculated according to eq.2. The mixture weighting factor, mean and variance are evaluated based on eqs. 3-5.

$$m_s = \frac{1}{N} \sum_{j=1}^{N} P(s, y_j) \qquad (3)$$

$$\mu_{y_s} = \frac{\sum_{j=1}^{N} y_j P(s|y_j)}{\sum_{j=1}^{N} P(s|y_j)} \qquad (4)$$

$$\sigma_{ys} = \frac{\sum_{j=1}^{N} P(s|y_j)(y_j - \mu_{y_s})(y_j - \mu_{y_s})}{\sum_{j=1}^{N} P(s|y_j)} \qquad (5)$$

The EM algorithm is designed to deal with closed form solution problem but it frames the image into different homogeneous regions. Based on the intensity of the homogenous regions, the high frequency components can be evaluated. The darker the regions, the larger the variance and hence more high-frequency components are available in the segmented regions of the image. Though several image segmentation algorithms are available we used the expectation maximization since it provides a simple, easy-to-implement and efficient tool for learning parameters of a model, and it also presents a mechanism for building and training rich probabilistic models for image processing applications [19].

2.2 Feature Extraction

The huge set of data available in images is simplified for analysis by the technique known as feature extraction. The number of variables in the large data set often causes several problems while analyzing the complex data. The complex data variables inturn require a large amount of memory and computation power which overfits the training sample and generalizes poor samples. Thus, feature extraction is one of the efficient method of constructing combinations of the data variables maintaining the data with sufficient accuracy.

DoG algorithm [9] was proposed by David Lowe in 1999. Difference of Gaussian (DoG) is a grayscale image enhancement algorithm that involves the subtraction of one blurred version of an original grayscale image from another less blurred version of the original image. The original gray scale images are convolved with Gaussian kernels having different standard deviations to obtain the blurred images. This process of blurring suppresses only high-frequency spatial information retaining the other information. The spatial information within the range of frequencies are preserved in both the blurred images. This kind of a technique is similar to a band-pass filter that discards all but a handful of spatial frequencies that are present in the original grayscale image.

While extracting features, the difference of Gaussian technique enhances the visibility of edges in a digital image. A wide variety of alternative edge sharpening filters operate by enhancing high frequency detail, but because random noise also has a high spatial frequency, many of these sharpening filters tend to enhance noise, which can be an undesirable artifact. Usually the high frequency detail that often includes random noise is removed by the DoG approach. The cost of extracting the features determined from the original is minimized by taking a cascade filtering approach, in which more expensive operations are applied only at locations that pass an initial test. The major stages of computation to generate the set of image features are:
Scale-space extrema detection: The overall scales and the image locations are determined in the initial state. DoG algorithms is applied to identify potential interest points that are invariant to scale and orientation.
Keypoint localization: At each candidate location, a detailed model is fit to determine location and scale from which the keypoints are selected based on measures of their stability [9].

To efficiently detect stable keypoint locations, scale-space extrema in the difference-of-Gaussian function is convolved with the image, D(x, y, σ), which can be computed from the difference of two nearby scales separated by a constant multiplicative factor k by using eq.6:

$$D(x,y,\sigma) = \left(G(x,y,k\sigma) - G(x,y,\sigma)\right) * I(x,y) = \mathrm{L}(\mathrm{x},\mathrm{y},\mathrm{k}\sigma) - \mathrm{L}(\mathrm{x},\mathrm{y},\sigma) \quad (6)$$

The local extrema in the DoG are found and by removing those with strong edge responses, the final results are selected as the feature points.

2.3 Orientation Assignment

Orientation assignment is the key step in achieving invariance to rotation as the keypoint descriptor can be represented relative to the orientation of the image [21]. Each circular region is made rotation invariant by defining a window centered at the chosen feature point. For all the pixels in the selected window, the gradients are computed and histogram of the gradient is determined. The peak of the histogram is selected as the orientation of the feature point, Θ(x, y) [8]. The scale of the keypoint is used to select the Gaussian smoothed image, L, with the closest scale, so that all computations are performed in a scale-invariant manner. For each image sample, L(x, y), at this scale, the gradient magnitude, m(x, y), and orientation, Θ(x, y), is pre-computed using pixel differences according to eq (7) and eq (8),

$$m(x,y) = \sqrt{\left(L(x+1,y) - L(x-1,y)\right)^2 + \left(L(x,y+1) - L(x,y-1)\right)^2} \quad (7)$$

$$\theta(x,y) = \tan^{-1}\frac{(L(x,y+1) - L(x,y-1))}{(L(x+1,y) - L(x-1,y))} \quad (8)$$

The magnitude and direction calculations for the gradient are done for every pixel in a neighboring region around the keypoint in the Gaussian-blurred image L. In the case of multiple orientations being assigned, an additional keypoint is created having the same location and scale as the original keypoint for each additional orientation.

2.4 *Image Normalization*

Image scaling is considered one of the fatal geometric attacks the image may undergo. Scaling can be either symmetric or nonsymmetric in which the scaling factor in *x* direction is different from the scaling factor in *y* direction [22]. The normalized image is assumed to have a predefined area and a unit aspect ratio. The aspect ratio γ of an image f(x,y) is defined using eq. 9 as,

$$\gamma = \frac{l_y}{l_x} \quad (9)$$

Where l_y and l_x are the height and the width of f(x,y), respectively. Let f ((x/a),(y/b)) be the rescaled image with γ=1 and area $\propto = (a/x)(b/y)$, where a and b are the required scaling factors (eq. 10)

$$al_x = bl_y \quad (10)$$

where a and b, are determined using eq (11) as,

$$a = \sqrt{\frac{\beta\gamma}{m_{o,o}}}, \quad b = \sqrt{\frac{\beta}{\gamma m_{o,o}}} \quad (11)$$

Transforming the image into its standard form requires translating the origin of the image to its centroids. By using eq. 12 the coordinates (x,y) are changed into (x’,y’),

$$\acute{x} = \frac{x-\bar{x}}{a}, \quad \acute{y} = \frac{y-\bar{y}}{b} \quad (12)$$

The image in the new coordinates system has aspect ratio γ=1 and area α.
Several remarks need to be mentioned at this point.

- The normalizing scheme does not need the original image for implementing the normalization at the decoder which adds a great advantage to the system.
- The normalized image suffers from smoothing effect which is a direct result of the interpolation that occurs in scaling and rotation correction.

With the scaling normalization, the aligned circular regions can be transformed to its compact size. Therefore, the selected circular regions are scaling invariant and are ready for watermark embedding. Based on the above analysis, the rotation and scaling invariant regions can be located in the image for watermark embedding. Because each region is a homogeneous area and its mean vector and covariance matrix have been calculated during the image segmentation, this information can help guide the watermark embedding process.

2.5 Watermark Embedding and Extraction

In the process of DWT watermark embedding, a bit stream of length L is transformed into a sequence W(l)…..W(L) by replacing the 0 by –1 and W(K) €{-1,1} (k=1,...,L), used as the watermark. The original image is first decomposed using Haar filter into several bands using the discrete wavelet transformation with the pyramidal structure. The watermark is added to the largest coefficients in all bands of details which represent the high and middle frequencies of the image [24]. Let f(m,n) denote the DWT coefficients which are not located at the approximation band LL of the image. The embedding procedure is performed according to eq. 13.

$$f^1(m,n) = f(m,n) + \alpha f(m,n) W(k) \qquad (13)$$

Where, α is the strength of the watermark, controlling the level of the watermark W(1)….W(L). By this embedding, DWT coefficients at the lowest resolution which are located in the approximation band are not modified. The watermarked image is obtained by applying the Inverse Discrete Wavelet Transform (IDWT). Figure 2 shows the block diagram of the embedding method.

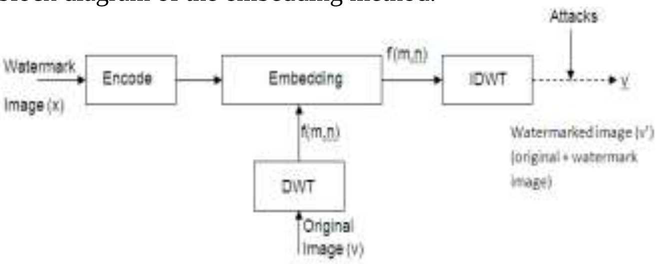


Figure 2 Block Diagram of the embedding method

In the watermark extraction procedure, both the received image and the original image are decomposed into the two levels. It is assumed that the original image is used for extraction. The extraction procedure shown in Figure 3 is described by the formula given in eq. 14

$$W_r(k) = \left(f_r^1(m,n) - f(m,n)\right) / \left(\alpha f(m,n)\right) \qquad (14)$$

Where, fr′(m,n) are the DWT coefficients of the received image. Due to noise added to the image by attacks or transmission over the communication channel, the extracted sequence $W_r(1)......W_r(L)$ consists of positive and negative values. Hence, the extracted watermarks are modified according to eq. 15.

$$W_e(k) = \mathrm{sgn}(W_r(k)) \qquad (15)$$

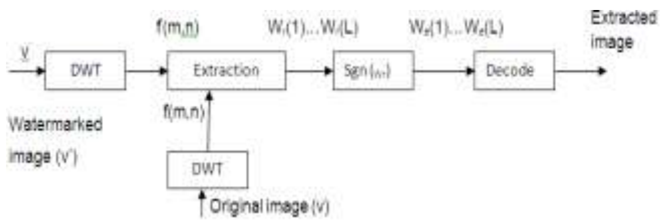


Figure 3 Block Diagram of the extraction method

3. Optimization Techniques

The goal of applying optimization in watermarking is to resolve the conflicting requirements of different parameters and properties of digital images. The balance between the watermark robustness and transparency has been one of the defying task for watermarkers and as a result, there is an urgent requirement for using powerful computation and optimization techniques that guarantee the watermarking performance. Optimized watermarking methods are discussed in this section based on theoretical derivations of algorithms with the aid of evolutionary computing techniques like Genetic Algorithm (GA), Particle Swarm Optimization (PSO) and Hybrid Particle Swarm Optimization (HPSO).

3.1 Genetic Algorithm

Genetic Algorithm (GA) is a search technique for determining the global maximum/minimum solutions for problems in the area of evolutionary computation. Although the GA operation performs randomly, choosing candidates to avoid stranding on a local optimum solution, there is no guarantee that the global maximum/minimum will be found [25]. The probability and the possibility of obtaining the global optimal solution by using GA are based on the complexity of the problem. Inspite of these difficulties, GA have been successfully applied to obtain good solutions in several applications. Any optimization problem is modeled in GA by defining the chromosomal representation, fitness function, and application of the GA operators. The GA process begins with a few randomly selected genes as the first generation, called population. Each individual in the population corresponding to a solution in the problem is called chromosome, which consists of finite length strings. The objective of the problem, called fitness function, is used to evaluate the quality of each chromosome in the population. Chromosomes that possess good quality are said to be fit and they survive and form a new population of the next generation. The three GA operators, selection, crossover, and mutation, are applied to the chromosomes repeatedly to determine the best solution over successive generations [26].

In digital image watermarking, the population is initialized by choosing a set of random positions in the cover image and inserting the watermark image into the selected positions. The optimal solutions for digital watermarking using DWT are obtained based on two key factors: the DWT sub-band and the value of the watermark strength factor [11]. The GA algorithm searches its population for the best solution with all possible combinations of the DWT sub-bands and watermark amplification factors. The host image taken into consideration is decomposed into four sub-bands with different resolutions. The decomposition process can be performed at different DWT levels, first, second, third, or higher. The optimal subband is determined by GA as follows: The first level produces 4 sub-bands, the second level takes each sub-band of the first level and decomposes it further into four sub-bands resulting in 16 sub-bands. Similarly, the third DWT level decomposes each second level sub-band into 4 subbands, giving a total of 64 sub-bands. The genetic algorithm procedure will attempt to find the specific sub-band that will provide simultaneous perceptual transparency and robustness. Inorder to improve the robustness of the algorithm against attacks, the watermark strength or the amplification factor α should be optimized, but this factor varies on each sub-band. The fitness function is formed based on the parameters Peak Signal to Noise Ratio (PSNR) and the correlation factor ρ (α * NC) as shown is Eq. 16. Here, the correlation factor is the product of Normal Correlation (NC) and the watermark strength factor α. The fitness function increases proportionately with the PSNR value, but NC is the key factor contributing to the robustness and ultimately, the fitness value increases with the robustness measure. The correlation factor ρ has been multiplied by 100 since its normal values fall in the range 0 ~ 1, where as PSNR values may reach the value of 100.

$$Fitness\ Function = PSNR + 100 * \rho \qquad (16)$$

where, PSNR in decibels (dB) is computed as shown in eq. (17):

$$PSNR_{AB} = 10\log\left(\frac{MAX_i^2}{MSE}\right) = 20\log_{10}\frac{MAX_i}{\sqrt{MSE}} \qquad (17)$$

Here, MSE = the mean square error between the original image and the watermarked image

MAXi = the maximum pixel value of the image which is generally 255 in our experiment since pixels were represented using 8 bits per sample.

The fitness function is evaluated for all the individuals in the population and the best fit individual along with the corresponding fitness value are obtained. Genetic operators like crossover and mutation are performed on the selected parents to produce new offspring which are included in the population to form the next generation. The entire process is repeated for several generations until the best solutions are obtained. The correlation factor ρ measures the similarity between the original watermark and the watermark extracted from the attacked watermarked image (robustness). The correlation factor ρ is computed using eq. 18 shown:

$$\rho(W,\hat{W}) = \frac{\sum_{i=1}^{N} W_i, \hat{W}}{\sqrt{\sum_{i=1}^{N} W_i^{\,2}}\sqrt{\sum_{i=1}^{N} \hat{W}_i^{\,2}}} \qquad (18)$$

Where, N denotes the number of pixels in the watermark, w and wˆ represent the original and extracted watermarks respectively. The procedure for implementing digital image watermarking using GA is shown below:

Initialize watermark amplification factor α between 0 and 1, initialize the population

Generate the first generation of GA individuals based on the parameters specified by performing the watermark embedding procedure. A different watermarked image is generated for each individual.

While** max iterations have not reached **do

Evaluate the perceptual transparency of each watermarked image by computing the corresponding PSNR value

Apply a common attack on the watermarked image.

Perform the watermark extraction procedure on each attacked watermark image.

Evaluate robustness by computing the correlation between the original and extracted watermarks

Evaluate the fitness function for the PSNR and ρ values

Select the individuals with the best fitness values.

Generate new population by performing the crossover and mutation functions on the selected individuals.

End While

The parameters like robustness, transparency, fitness value, CPU time and elapsed time are determined using genetic algorithm when the watermark images are attacked by filtering, scaling, rotation, and JPEG compression.

3.2 Particle Swarm Optimization

Particle Swarm Optimization (PSO) is a scheme for optimizing functions based on the allegory of social behavior of flocks of birds and schools of fish. It was first designed to simulate birds seeking food which is defined as a cornfield vector [27]. An individual bird in the flock would find a path for food through social cooperation with other birds around it. No bird is a leader, if one bird changes its style of flying all the other follow the same. In digital watermarking, for each time step a particle has to move to a new position, by adjusting its velocity. The movement is adjusted in the direction of its best current velocity or according to the direction of the neighborhood best. Having worked out a new velocity, its position is simply its old position plus the new velocity. PSO algorithm takes each particle in the swarm representing a solution to the problem and it is defined with its position and velocity. In D-dimensional search space, the position of the i^{th} particle can be represented by a D-dimensional vector, present []= ($present_{i1}$,…, $present_{id}$, …, $present_{iD}$). The velocity of the particle $v_{[]}$ can be represented by another *D*-dimensional vector $V_{[]}$= (V_{i1},…, V_{id}, …, V_{iD}). The best position visited by the i^{th} particle is denoted as $gbest_i$=($gbest_{i1}$,…,$gbest_{id}$,…,$gbest_{iD}$), and P_g as the index of the particle visited the best position in the swarm, then gbest becomes the best solution found so far, and the velocity of the particle and its new position will be determined by the following equations.

$$V[\,] = Co * V[\,] + C1 * rand(\,) * (pbest[\,] - present[\,]) + C2 * ran \qquad (19)$$

$$present[\,] = present[\,] + v[\,] \qquad (20)$$

The PSO algorithm for digital image watermarking tries to determine optimal Scale Factors (SFs). The transparency and robustness can be achieved by optimizing these scaling factors. While applying PSO to digital image watermarking, each string (combinations of 1s and 0s) in the swarm represents a possible solution to the problem with a set of SFs [28]. The scale factors for the initial swarm solutions are generated in a random manner. If the pixel values of the watermarked image are out of the desired range, then they are, rescaled based on the host image pixel values.

There are various signal processing and image processing operations for which the robustness has to be evaluated. The robustness and transparency of the proposed watermarking algorithm is evaluated in this paper using the attacks that are commonly employed in literature such as filtering, Gaussian noise, rotation, scaling and JPEG compression. In PSO optimization procedure, the attacking scheme refers to removing the extracted image after adding noise.

The watermarks are computed from the attacked watermarked images using the extraction procedure. The two dimensional correlation values are calculated between the original and watermarked images (*corrI*= *corr*(*I*, *IW*)) and between the original watermark and the extracted watermarks (*corrW*= *corr*(*W*,*W**)). The correlation values are then feed backed to PSO to evaluate the appropriateness of the SFs. The appropriateness of a solution is calculated depending on both the transparency (*corrI*) and the robustness (*corrW*) under noise attack at each iteration of optimization process as mentioned above. The objective function to be minimized is defined as:

$$f_i = \left[\frac{1}{\frac{1}{t}\sum_{i=1}^{t} \max(corr_{Wi}(W, W_i^*)} - corr_I(I, I_W) \right]^{-1} \quad (21)$$

where, $corr_I$ and $corr_W$ are related to transparency and robustness measure, respectively; *fi* and *t* are the objective value of the i^{th} solution and the number of attacking methods, respectively. Since each watermark pixel is embedded into each corresponding sub-band, maximum value of correlations (max(*corrW*)) is considered in the calculations. The processes explained above are repeated until a predefined stopping criterion is satisfied, for example maximum iteration number. The pseudocode of the PSO for DWM is shown below:

Initialize swarm size, acceleration constant and inertia weight of the swarm
Generate the initial swarm randomly
While *stopping condition is false* **do**
Present the watermarked images into the swarm population
Apply attacks on the watermarked images and extract the watermarks
Compute the similarity between the watermark and the extracted ones
Evaluate the objective function
Feedback the appropriateness value to the PSO to get new values
End While

The swarm size, acceleration constant and inertia weight of the swarm are initialized. The watermarked images are produced using the solutions in the swarm by means of embedding process. The Normalised Correlation (NC) values are computed between the host image and each watermarked images. The attacks are applied upon the watermarked images one by one and the watermarks are extracted from the attacked images using the extraction procedure. The objective function is evaluated and the procedure is repeated until a constant number of generations are reached. In our experiment, by using Particle Swarm Optimization the fitness function is determined by evaluating the quality of each solution, so that individuals with high quality will survive to the next swarming process and the parameters like fitness value, CPU time and elapsed time are determined from the watermarked image.

4 Result Analysis

The experimental analysis and simulation determine the efficiency and capability of the work. In this section, the simulation results for various modules implemented namely, image segmentation, feature extraction, orientation assignment, image normalization, watermark embedding and extraction, optimization techniques like Genetic Algorithm, Particle Swarm Optimization and Hybrid Particle Swarm Optimization are explained to quantify the benefits of digital watermarking in image processing.

4.1 Image Segmentation

To evaluate the performance of proposed scheme, set of 50 texture images were chosen among which 512x512 images were taken as the original image and 256x256 images as the watermark image. The purpose of image segmentation is to partition an image into meaningful regions with respect to a particular application. The segmentation is based on measurements taken from the image and might be grey level, colour, texture, depth or motion. Using the EM segmentation, the image is segmented into number of homogeneous regions and the parameters are updated for each segmented regions.

The original image *house.tiff* is segmented into five different homogeneous regions, and each segmented region is represented based on colors. The variance of the regions are high if the region contains more dark regions. This implies that the darker sections contain more high frequency components. Figures 4 and 5 show the original and the segmented images of *house.tiff* using EM segmentation.

Figure 4 Original Image

Figure 5 Segmented Image

Table 1 EM Image Segmentation

Class	Mean	Variance
K=1	118.8056	0.003
K=2	13.3041	0.0139
	144.8486	1.4098
K=3	12.9443	0.0101
	123.1324	1.9331
	166.2306	0.1464
K=4	12.8613	0.0094

	108.3290	2.8983
	168.0908	0.1282
	132.8610	0.2781
K=5	12.7761	0.0089
	45.1680	0.4034
	127.3312	0.4092
	167.5977	0.1388
	188.2837	1.1109

Table 1 shows the value for mean and variance of the segmented image determined for each segment or class. The covariance can be set as the identity matrix and the mean is calculated by finding the average of different regions of the image. From the table, it is found that as the number of regions increase, the mean and variances of the segmented regions are also increased and this indicates the strength of the segmented region to embed the watermark image.

4.2 Feature Extraction

Difference of Gaussian (DoG) is a grayscale image enhancement algorithm to select the feature points from the segmented image. This algorithm computes the difference between one blurred version of the original grayscale image and another less blurred version of the original image. The difference of Gaussians is similar to a band-pass filter that discards all the coefficients but a handful of spatial frequencies are present in the original grayscale image. The parameters used in the DOG algorithm and their values are,

Smoothing parameter (s_p) – fixed
Radius (r) – 10
Sigma (σ) – [0-200]

Table 2 Gaussian values for Original and Blurred image

Sigma	G (diff of original image)	G1 (diff of blurred image)	g (Gaussian of original image)	g1 (Gaussian of blurred image)
70	0.0057	0.0040	255	255
80	0.0050	0.5902	255	78
90	0.0044	0.0031	255	24
100	0.0040	0.0028	255	11
110	0.0036	0.0026	97	6

The scale space extreme for the original and blurred image to extract the feature points is given by taking difference of Gaussian values as shown in Table 2. The local extrema in the DoG are found and by removing those with strong edge responses, the final results are selected as the feature points. DoG algorithm is chosen in our experiment to find the extracted points since, in each segmented region, one feature point is selected and the circular region centered at the selected feature point with radius will be used for the watermark embedding and detection. After the reference feature points are selected, the rotation and scaling invariant properties are assigned to the circular regions centered at the selected feature points.

4.3 Orientation Assignment

The circular regions are chosen and are made rotation invariant using orientation assignment. In order to achieve orientation invariance, the coordinates of the descriptor and the gradient orientations are rotated relative to the keypoint orientation. By finding the image gradients as in Figure 9, the key points in the image are extracted and modified to reduce the illumination change.

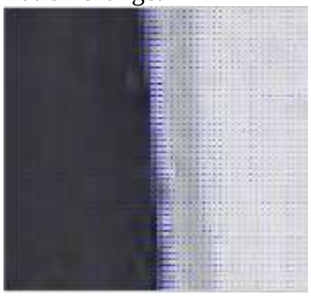


Figure 6 Gradient of the image

4.4 Image Normalization

A technique for normalizing an image against geometric manipulation is implemented and the purpose is to obtain scaling, rotation invariance for the image during watermark embedding and extraction phases. Scaling normalization is employed to acquire the scaling invariance for the circular region. It transforms the image into its standard form by translating the origin of the image to its centroid(x,y). The normalized form of the *house.tiff* image is shown in Figure 7. In this figure, the normalization effect of the image is evaluated using local mean and standard deviation estimated by Gaussian kernel with sigma = 4.

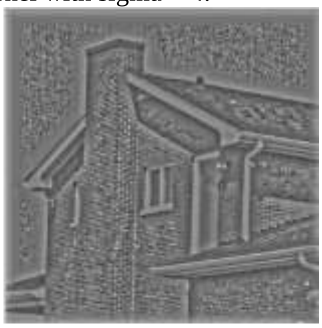


Figure 7 Normalised image

4.5 Watermark Embedding and Extraction

For watermark embedding and extraction using DWT, original image '*house.tiff*' with size 256x256 is taken as a cover image and the watermark image '*best.bmp*' with size 60x24 is taken as the image to hide as shown in the Figure 8 and Figure 9 respectively. The image is decomposed into sub-image of different spatial domain and independent frequency distinct, and the resultant image will be of low pass-low pass (LL) images in the upper left corner, the low pass-high pass (LH) images on the diagonals and the high pass-high pass (HH) in the lower right corner. The process will continue to run the same wavelet transform on the low pass-low pass version of the image to get sub images.

The original image is first decomposed into several bands using the discrete wavelet transformation with the pyramidal structure. The sub-band LL represents the coarse-scale DWT coefficients while the sub-bands LH, HL and HH represent the fine-scale of DWT coefficients. If the information of low-frequency distinct is DWT transformed, the sub-level frequency distinct information will be obtained. The watermark is added to the largest coefficients in all bands of details which represent the high and middle frequencies of the image. The watermarked image by Discrete wavelet transform is shown in the Figure 10.

The parameters used for embedding the watermark into the cover image using DWT are,
Part – Decomposition
Data - input image
Mode - type of image (tiff,bmp.jpg,jpeg,png)
Level - 3

In the watermark extraction procedure both the received image and the original image are decomposed into the two levels. In the first level the image is filtered by lowpass, highpass filters and the lowpass region is further filtered by both (LP and HP) filters in second level to obtain the LL plane.

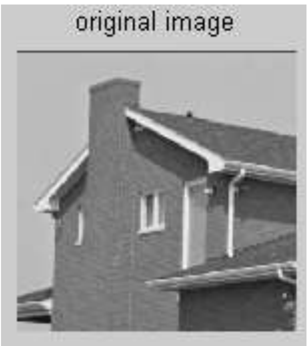


Figure 10 Original Image

Figure 11 Image to Hide

Figure 12 Watermarked Image

4.6 Optimization in Watermarking

This section illustrates the implementation and simulated results of the computational intelligence techniques applied for digital image watermarking.

Genetic Algorithm

The GA training procedure was executed with an initial population size of 120. The watermark bits of the '*best.bmp*' are inserted into the cover image '*house.tiff*' and this forms the initial population. The fitness function is evaluated based on the PSNR and the CPU time, and the elapsed time is determined. The crossover rate is 0.9 with single point crossover and the mutation rate is 0.02 with the flip bit type of mutation. The GA procedure is repeated until the maximum number of generations, 100 are reached. The watermark amplification factor is initially set as 0.5, as the generations progress, the value varies with respect to the sub-bands. The same GA procedure was tested on 6 different images chosen in a random manner from a set of 50 images with the same watermark image. The parameters used for digital watermarking using GA are shown below:

Population size : 120 (multiples of 4)
Crossover probability: 0.9
Mutation probability : 0.02
Type of crossover : Single point crossover
Type of mutation : Flip bit
Number of generations: 100

Table 3 Fitness Value and Best Point of the Extracted Watermark Image using GA

Watermark Images	Fitness value	CPU time (sec)	Elapsed time (sec)
House.tiff	1.0e+006	14.8760	17.5560
Rice.png	1.0e+007	13.0313	16.1316
Fingerprint.bmp	1.0e+007	19.4563	21.6565
Stone.jpg	1.06e+006	11.5713	14.5175
Goldhill.bmp	1.02e+007	15.4973	13.5783
Zoneplate.bmp	1.01e+007	14.1345	19.3285
Lena.tif	1.0e+006	12.1874	16.7832

The fitness value, CPU time and the elapsed time are computed for a set of images as shown in Table 3. The fitness value increases proportionately with the PSNR value and the watermark amplification factor α. The GA procedure was also tested with filtering attacks, JPEG compression, rotation and scaling attacks. The results are discussed in the following sections.

Particle Swarm Optimization

The initial particles are formed by embedding the chosen watermark image bits into the cover image, which comprises the initial population. The particle size in our simulation is chosen as 36, if the particle size is larger, more points can be searched in the search space to determine the global optimal solution, but this increases the number of iterations and hence the computational time. Based on several simulation results, we choose the cognitive factor c_1=1.8 and social coefficient factor c_2=2, and inertia weight *w*=0.3. The algorithm terminates after 200 iterations in accordance with various experimental observations. The parameters and their values of the PSO algorithm for watermarking optimization are configured as follows.

Cognitive factor, c_1 : 1.8
Social coefficient c_2 : 2
Inertia weight, w : 0.3
Particle size : 36
Number of generations: 200

Table 4 Fitness value and best points of the extracted watermark image using PSO

Images	Fitness value	CPU time (sec)	Elapsed time (sec)
House.tiff	1.05e+006	12.543	14.454
Rice.png	1.21e+007	13.0313	15.4042
Fingerprint.bmp	1.0e+007	18.4563	21.3362
Stone.jpg	1.06e+005	14.5713	17.2371
Goldhill.bmp	1.04e+006	11.5213	15.1713
Zoneplate.bmp	1.02e+007	19.3463	21.3243
Lena.tif	1.03e+007	02.1138	03.1271

The fitness value and the computational time for the chosen set of images in PSO based digital watermarking are shown in Table 4.

4.7 Attacks

To evaluate the performance of the optimization techniques, several experiments were conducted using the set of host images and a single watermark image. The common attacks employed to the watermarked image here are filtering, addition of Gaussian noise, rotation, scaling and JPEG compression. The two dimensional correlation values are calculated between the original and watermarked images (*Transparency measure*) and between the original watermark and the extracted watermarks (*Robustness measure*). The GA, and PSO procedures were repeated by applying these attacks and the robustness measure was evaluated.

Filtering attacks

The watermarked image under consideration *house.tiff* is subject to several types of filtering like average filtering, Gaussian filter, median filtering, and Wiener filtering which are regarded as attacks. The mask for the filter is usually a window which can take various sizes. Average filtering removes the high frequency components present in the image acting like a low pass filter. The average filter with a 5 x 5 mask was applied to the watermark image during the optimization process of GA, and PSO to evaluate the robustness measure. While using Gaussian filter attack, the mean was set to '0' and the variance set to '1', with a window size 3 x 3. The median filtering was applied four times on the watermarked image with a mask size of 3 x 3, and this seems to preserve the edges while recovering the watermark. Wiener or adaptive noise removal filtering is an adaptive process tailoring itself to the local image variance which is inversely proportional to the smoothing process. This works best in removing the Gaussian white noise and in our experiment the mask size was set to 3 x 3. Table 5 shows the attacked watermarked image with different types of filtering attacks. The correlation factor is evaluated based on the similarity between the original watermark and the attacked watermark for all the filtering techniques and tabulated. The results show that the PSO watermark optimization technique has the best similarity of extracted watermarks among the compared approach such as GA.

Additive Noise

A Gaussian noise was added to the watermarked image with zero mean and different variance σ, indicating the percentage of gray levels added into the image. The robustness measure is computed by varying σ between [0.001, 1] for GA, and PSO algorithms as indicated in Table 6.

Table 5 Computed robustness for Filtering Attack

Optimization Technique	Average Filtering	Gaussian Filtering	Median Filtering	Adaptive Noise Removal Filtering
Watermarked Image				
Robustness measure using GA	0.972	0.989	0.995	0.992
Robustness measure using PSO	0.921	0.979	0.994	0.984

Table 6 Evaluated Results for Gaussian noise Attack

Gaussian Noise	σ=0.001	σ=0.01	σ=0.1	σ=0.5	σ=1
Watermarked Image					
Robustness measure using GA	0.875	0.871	0.864	0.821	0.81
Robustness measure using PSO	0.887	0.882	0.879	0.862	0.842

Table 7 JPEG Compression Attack and robustness computation

JPEG Compression Quality Factor	10%	20%	36%	50%	70%	85%	95%
Watermarked Image							
Robustness measure using GA	0.823	0.845	0.878	0.889	0.894	0.910	0.936
Robustness measure using PSO	0.872	0.884	0.891	0.917	0.930	0.952	0.972

Table 8 Robustness Results for Rotation Attack

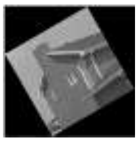
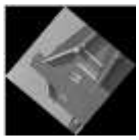
Degree	5º	10º	20º	30º	40º	50º
Watermarked Image						
Robustness measure using GA	0.88	0.82	0.75	0.658	0.595	0.545
Robustness measure using PSO	0.93	0.912	0.9	0.856	0.823	0.78

Table 9 Experimental Results for Scaling Attack

Scale Factor	0.5	0.75	0.9	1	1.2	1.5	2
Watermarked Image							
Robustness measure using GA	0.786	0.825	0.932	0.987	0.86	0.789	0.753
Robustness measure using PSO	0.833	0.947	0.984	0.996	0.953	0.811	0.712

JPEG Compression

JPEG is one of the most widely used lossy compression algorithms, and any watermarking technique should be resilient to some degree of JPEG compression attacks. For images that are published on the internet, robustness of watermarks against the JPEG compression standard is particularly important. In general, such lossy compression algorithms discard the redundant and perceptual insignificant information during the coding process, but watermark embedding schemes add invisible information to the image. JPEG compression calculates the visual components based on the relationship with the neighboring pixels in the image. The specific positions to embed the watermark are derived from these visual components which are proportion to the quality levels of the JPEG compression. In practice, it is difficult to choose the minimal quality factor (QF) of JPEG for compression. Low values of quality factor indicate high compression ratio and vice versa. The Quality Factors (QF) were set from 10% to 95% for simulation, and the results are shown in Table 7. The watermark was detected well even after the image was compressed using a quality factor of 10%. The correlation factor seems to be high for the quality factor of 95%, indicating that the similarity values prove best match between the original watermark and the extracted watermark. The robustness measure is 0.989 when the PSO algorithm is applied to optimize the watermarking process and this shows that the proposed hybrid watermarking technique is superior to GA whose robustness measure is 0.936.

Rotation

Geometric attacks usually make the watermark detector loose the synchronization information and one of the major attacks among this group is rotation. The watermarked image is rotated by an angle in the counterclockwise direction before extracting the watermark. The watermarked image is rotated by angles 5º, 10º, 20º, 30º, 40º and 50º to the right and then rotated back to their original position using bilinear interpolation. While rotating, the black pixels left after rotation in the corners have been included to maintain the image size and the shape. For larger angles, more black pixels are padded and hence the correlation factor or the robustness measure tends to decrease. For each degree of rotation, the correlation factor was measured between the original watermark and the attacked watermark to determine the degree of similarity between them. Table 8 shows the watermarked image rotated for a set of angles and the corresponding robustness measure while applying GA, and the PSO algorithm. It can be inferred that the watermarked image is robust against rotation attack when PSO algorithm is applied since the correlation factor is 0.93 denoting more similarity features between the watermark image and the attacked watermark image.

Scaling

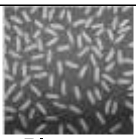
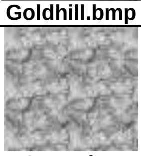
Scaling is generally considered more challenging than other attacks due to the fact that changing the image size or its orientation even by slight amount, could dramatically reduce the receiver ability to retrieve the watermark. The scaling factors are selected such that the robustness, invisibility and quality of the extracted watermark is maintained, usually higher in the low frequency band and lower in the high frequency band. In our experiment, the watermarked image was scaled by using different scale factors within the range [0.5, 2] as shown in Table 9. For a reasonable range of the scale factor, the applied optimization techniques are robust to the scaling concept.

The experiments were conducted on a set of images and the transparency measure is computed for the images house.tiff, rice.png, fingerprint.bmp, goldhill.bmp, stone.jpg and lena.tif and the results are tabulated. Table 13 shows the computed values of perceptual transparency when the optimization techniques are applied to the corresponding set of images. The invisibility and fidelity are comparatively high for the PSO technique (transparency=0.9994) for *house.tiff*, which is closer to one when compared against GA.

5. Conclusion

Digital image watermarking algorithms based on the discrete wavelet transform (DWT) have been widely recognized to be more prevalent than the existing steganographic techniques. In this paper, several pre-watermarking stages were included to enhance the quality and to maintain the invariance property of the image to be watermarked. The watermarked image was optimized using computational intelligence techniques like GA, and PSO and the performance was compared. Imperceptibility of images and robustness of abstracting digital watermark are an important criterion of judging digital watermarking algorithm. Inorder to prove this, several attacks were imposed on the watermarked image and optimized using the evolutionary algorithms. The PSO algorithm seemed to yield a better watermark, invisible to the human eye, when filtering attacks were applied. The fact that geometrical attacks like rotation and scaling are more stronger than filtering attacks is proved from the results obtained in Table 11 and 12. In JPEG compression attacks, the extracted watermarks are fully recognizable with PSO with quality factors between the ranges 10% and 95%. The experiments and results show that the PSO is not only robust to attacks, but also ensures the imperceptibility and fidelity of the watermark embedded image. The experiments can still further be expanded with additional attacks like stirmark, image enhancement, JPEG2000, translation and also a combination of attacks can be imposed to understand the performance of the optimization techniques in a better perspective.

Table 13 Comparison of optimization techniques based on transparency measure

Optimization Technique	Transparency Measure using GA	Transparency Measure using PSO
 House.tiff	0.9989	0.9994
 Rice.png	0.9988	0.9990
 Fingerprint.bmp	0.9986	0.9990
 Goldhill.bmp	0.9987	0.9989
 Stone.jpg	0.9990	0.9992
 Lena.tif	0.9989	0.9993

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