Improve Wavelet Threshold Selection Based on PSO Algorithm and Successive –Approximation Method in Image Compression Applications

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Abstract

The growing rate in the applications that use the image compression such as the internet, multimedia, satellite imaging, medical imaging etc., make this subject under heuristics of researchers. So, this field of image compression has been continuous to grow rapidly at the last years. From the compression point of view, the wavelet transform plays an important role and a dominant technology in the fields of signal and image processing. It helps us precisely decompose the signal into low and high frequency components making the thresholding process for redundant data done in an efficient way. Also, the threshold value selection method performs a major part in data compression system. Therefore, in this paper, two approaches have been proposed. The first one depends on implementation the discrete wavelet transform (DWT) with Particle Swarm Optimization (PSO) algorithm to get a good selection for the threshold. The second is a new successive-approximation threshold (SA-thresh) selection method used to produce the global threshold value for the wavelet detail coefficients of the image. These proposed methods give more improvement in compression ratio (CR) for the image as well as enhancement in the peak signal to noise ratio (PSNR). The implementation of this work has been done by using *MATLAB 2011a*.

Keywords:Discrete Wavelet Transform (DWT),Particle Swarm Optimization (PSO),image compression, threshold selection, successive-approximation.

الخلاصة:

ان معدل النمو في التطبيقات التي تستخدم تقنية ضغط الصور مثل (الانترنيت، الوسائط المتعددة، تصوير الاقمار الصناعية، التصوير الطبي ،الخ..) جعل هذا الموضوع تحت عناية الباحثين ، ولذا فان هذا المجال من تقنية ضغط الصور استمر بالتطور السريع خلال السنوات الاخيرة. من وجهة نظر عملية الضغط فان تحويلة المويجات تلعب دورا مهما وتقنية بارزة في مجال معالجة الاشارة والصور. فهي تساعد بدقة على تحليل الاشارة الى مركبات تردد واطئة وعالية لتجعل عملية عتبة البيانات الفائضة تتم بطريقة كفوءة. كذلك فان طريقة اختيار قيمة العتبة يشكل جزء اساسي في نظام ضغط البيانات . بناء على ذلك ، في هذه الورقة ، اقترحت طريقتين . الاولى تعتمد على تنفيذ تحويلة المويجات المتقطعة مع خوارزمية سرب الجسيمات للحصول على اختيار جيد لقيمة العتبة. الطريقة الثانية هي طريقة جديدة تستعمل لاختيار العتبة بالتتابع التقريبي لتوليد قيمة العتبة العامة للعوامل التفصيلية للصورة. هذه الطرق المقترحة تعطي اكثر تحسين في نسبة ضغط الصور وايضا تعزز نسبة اعلى قمة اشارة الى الضوضاء. ان تنفيذ هذا العمل قد تم باستخدام الماتلاب ٢٠١١ ا.

الكلمات المفتاحية: تحويلة المويجات المتقطعة، خوارزمية سرب الجسيمات، ضغظ الصور، اختيار العتبة، التتابع التقريبي

1. Introduction

Compression data represents a key technology in transmission bandwidth and/or storage capacity demands. A more compressed data result in more bandwidth available and more capacity achieve. As long as the compression method done in an efficient way, the target behind these demands will be satisfied. Images, especially color images, have a huge information and redundancy data. Therefore, if we need to transmit or store such images we will need a more channel bandwidth and a large amount of storage capacity, respectively. So that, we need to apply the image compression technique as a solution to confront this problems. The main task of this technique are reducing the redundancy in image (there are two types of redundancy here, the first one called *psycho visual redundancy*: results from the irrelevant information that cannot be perceived or noticed to the viewer. The second is *spatial redundancy*: results from the correlation between the neighboring pixels) (Ida *et al,* 2006) .Hence, by reducing these types of redundancy the number of bits required for representing the image will be minimized. However, to make a reduction in redundant data, at first the image should be transformed into its frequency domain (coefficients), this result in decorrelating the correlated pixels of the image, making the spatial redundancy type as less as possible.

Over the years, many techniques such as, Karhunen Loeve Transform (KLT), Discrete Fourier Transform (DFT), Discrete Cosine Transform (DCT) and Discrete Wavelet Transform (DWT) have been developed for analyzing the different frequency components within a signal. Each of which has own advantage and disadvantage (Kranthi *et al,* Naidu *et al,* 2014). In our work, we will use the DWT to decompose the image into high and low frequency components. This is accomplished by comparing the image with a set of template functions (basis functions) which obtained from the scaling and shifting of a base wavelet $\varphi(t)$ (called mother wavelet) and then looking for their similarities (Gao *et al;* Yan *et al,* 2011). Because of the fact that the human vision system are not much sensitive to the high frequency components in the image, it becomes possible to remove this redundant data from these components by thresholding it by a suitable threshold value and this will reducing the psycho visual redundancy type in image. So that, to get a better compression ratio for the image, the selection method for threshold value should be optimized.

In the last years , various thresholding methods have been developed such as (Mantosh *et al,* Hari *et al,* 2013) proposed an image threshold method that exploits the sub band dependency of the neighboring wavelet coefficients, (Pankaj *et al,* Swati *et al,* 2011) used the probabilistic model of the wavelet image coefficients to drive the value of threshold, and (Zhengmao *et al,* Habib *et al,*Yongmao *et al,*2009) used a PSO algorithm for three multilevel decomposition of the image and find the threshold for each level dependently.

In this paper, an optimum threshold selection based on the PSO algorithm and successive–approximation method were proposed. The objective measures represented by evaluating PSNR, MSE, and CR are calculated for the image at each value of threshold.

The organization of this paper achieved as follows: In the next section (2) a method of how the Discrete Wavelet Transform (DWT) applied to decompose the image into approximation and detail coefficients. Particle Swarm Optimization (PSO) has been covered in section (3). In section (4) the traditional and modified methods of the threshold selection has been studied. Section (5) discusses the algorithm steps and simulation result. Finally, the section (6) concluding this paper.

2. Discrete Wavelet Transform (DWT)

The basic idea of the discrete wavelet transform used for the (image) is described as follows: the image is divided into four sub bands (coefficients) arisen from applying four separable filters to the original image (Monika *et. al*, Alka *et. al*, 2014). These filters described by one *LPF* (represent the scaling basis function) and three *HPF* (represent the horizontal, vertical and diagonal wavelet basis function). These filters used to extract the low and high frequency components in the image respectively. The four filters (basis function) can be described as follows in equations (1), (2), (3), and (4) respectively (Zhengmao *et al,* Habib *et al,* 2009).

$$\varphi(x,y) = \varphi(x)\,\varphi(y) \tag{1}$$

$$\psi^{H}(x,y) = \psi(x)\varphi(y) \tag{2}$$

$$\psi^{V}(x,y) = \varphi(x)\psi(y) \tag{3}$$

$$\psi^{D}(x,y) = \psi(x)\psi(y) \tag{4}$$

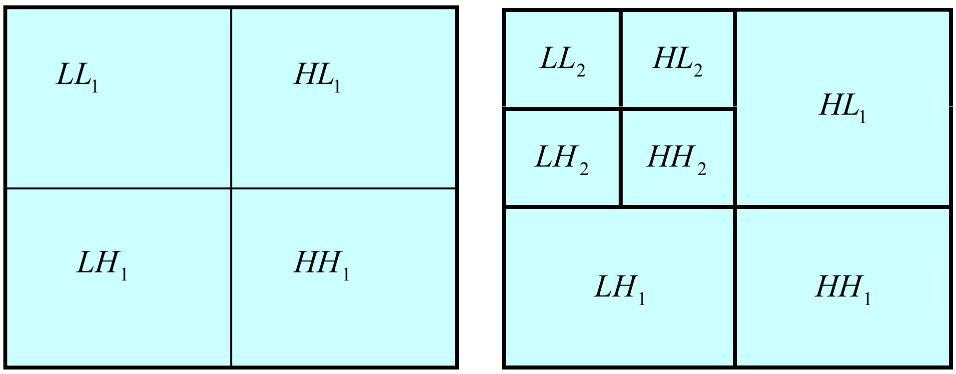
Where $\varphi(x)$ represents the scaling basis function, and $\psi(x)$ represents an orthonormal wavelet basis function.

However, The DWT of the two dimensional function $f(x, y)$ or image has a size M by N is described in equations (5), and (6).

$$w_{\varphi}(j_0, m, n) = \frac{1}{\sqrt{MN}} \sum_{x=0}^{M-1} \sum_{y=0}^{N-1} f(x, y)\, \varphi_{j_0, m, n}(x, y) \tag{5}$$

$$w_{\psi}^{i}(j, m, n) = \frac{1}{\sqrt{MN}} \sum_{x=0}^{M-1} \sum_{y=0}^{N-1} f(x, y)\, \psi_{j, m, n}^{i}(x, y) \tag{6}$$

Where: i = {H, V, D} index for horizontal, vertical and diagonal wavelet basis functions. j_0 = 0, represents the starting scale. $\varphi_{j_0, m, n}(x, y)$, represents the scaling basis function. $\psi_{j, m, n}^{i}(x, y)$, represents the wavelet basis functions. $w_{\varphi}(j_0, m, n)$, represents the coefficients that will be obtained from scaling basis function which is defined as the *approximation* coefficients. It displays the approximation of the (image) and labeled as LL_1. $w_{\psi}^{i}(j, m, n)$, represent the coefficients that will be obtained from the wavelet basis functions and are called the *detail* coefficients. They display the horizontal, vertical and diagonal details of the image. These are labeled as HL_1, LH_1 and HH_1 respectively as shown in figure (1a). However, these coefficients represent the 1-level decomposition of the image. To obtain the next decomposition level of the wavelet coefficients, the sub band LL_1 is farther decomposed as shown in figure (1b). This is called 2-level decomposition of the image. This process is repeated by farther decomposition for the coefficients in LL_2 if we want the third level decomposition and so on.



(a) **(b)**

Figure (1): a) 1-level decomposition, b) 2-level decomposition.

3. Particle Swarm Optimization (PSO)

The particle swarm algorithm is a swarm intelligence optimization algorithm. Also, it is an evolutionary computation algorithm which has been developed by Kennedy and Eberhert in 1995. It simulates the behavior of bird flocking together to seek the food source. While searching for the food source the birds communicate with each other to reach the target with minimum duration time. (Shet *et al,* Vrinda *et al,* 2015). The main aim of research in optimization is to design the most suitable and efficient algorithm for a given optimization task. In the image compression field, the one important advantage of using the optimization technique is to help us increase the compression ratio while keeping a good quality for the image (Karnthi *et al,* Naidu *et.*

al, 2014). To understand the main concept of the PSO algorithm, suppose we have two swarms flying in the sky, trying to reach a particular destination. To choose the proper path, each Particle in the swarm based either on the own best experience that has been saved in memory or on the experience of the best current particle in the swarm will choose the proper path for reaching the particular destination faster. Therefore, each particle will need to update its position and velocity continuously. Let us assume x_i and v_i as the position vector and velocity vector for the i^{th} particle respectively. The new velocity vector is determined by the following formula in equation (7):

$$v_i^{t+1} = wv_i^t + c_1\varepsilon_1(x_i^* - x_i^t) + c_2\varepsilon_2(g_i^* - x_i^t) \quad (7)$$

Then the new position can be updated as follows in equation (8):

$$x_i^{t+1} = x_i^t + v_i^{t+1} \quad (8)$$

Where: t is the counter of iteration, w is the inertia weight, ε_1 and ε_2 are uniform random numbers usually chosen between [0,1], c_1 is a positive constant called coefficient of the self-recognition component, c_2 is a positive constant called coefficient of the social component. Generally c_1 and c_2 called learning factors and their values usually chosen as $c_1 = c_2 = 2$, the index x_i^* represents the best fitness value of the particles and the index g_i^* belongs to the best particle among all particles in the swarm. The following steps represent the general pseudo code of the PSO algorithm:

1- Generate the objective (fitness) function $f(x)$
2- Initialize locations x_i and velocity v_i for n particles
3- Find g_i^* from min { $f(x_1), f(x_2), \ldots\ldots\ldots f(x_n)$ }
4- Take criterion as follows:
While t=t+1
(for) all n particles:

- generate a new velocity v_i^{t+1} using the equation (7)
- calculate new location x_i^{t+1} using the equation(8)
- evaluate the fitness function at new locations x_i^{t+1}
- find x_i^* (the best current location for each particle)

End the loop (for)

- find g_i^* (the best current global location)

End while

5- Output the final results x_i^* and g_i^*

4. The Traditional and Modified Threshold Selection Methods

Figure (2) shows the traditional process of image compression scheme.

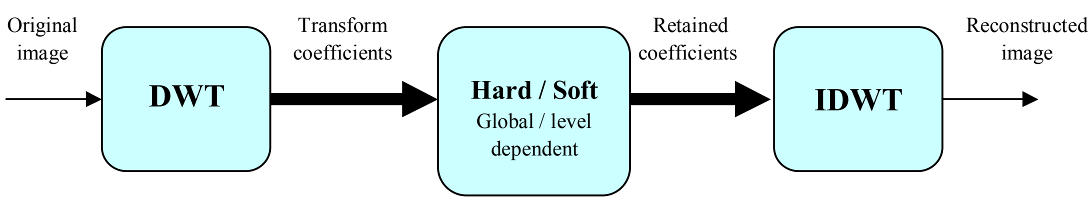


Figure (2): Traditional model of image compression scheme.

The compression process starts by transforming the original image from spatial domain (pixels) to transform domain (coefficients). This is done by applying the image into the DWT. This type of transformation depends on the type of wavelet that has been used and its level of decomposition. However, the DWT separated the information presented in the image into approximation coefficients represents the low frequency components of the image, and the detail coefficients represent the high frequency components. Due to the fact that human vision is much more sensitive to small variations in color or brightness that means that the human vision is more sensitive to low frequency component. Therefore only high frequency components in an image can be compressed without distortion. Therefore, the next step in the process is the thresholding process of the detail coefficients which leads to remove some redundancy from high frequency component. There are two main types of thresholding technique: hard and soft thresholding, if we denoted to the *ith* coefficient by C_i then the following formula in equations (9) and (10) describes the two main types respectively (*Grace et al,, Bin et al, 2000*).

Hard threshold: eliminates all coefficients C_i that are smaller than the threshold value (T). If we denote the retained coefficient by C_i^* then:

$$C_i^*(T) = \begin{cases} C_i & \text{if } C_i < T \\ 0 & \text{otherwise} \end{cases} \tag{9}$$

Soft threshold: The soft threshold leads to less distortion of the image than hard threshold and it's written as follows:

$$C_i^*(T) = \operatorname{sgn}(C_i) * \max(|C_i| - T), 0) \tag{10}$$

However, the threshold process modifies the coefficients as the per selected threshold value. In the traditional system, two famous approaches available depending on the threshold selection: the first consists of taking the wavelet expansion of the image and keeping the largest absolute value of coefficients, in this case we can set a global threshold for the image. The second uses a three orientation thresholds horizontal, vertical and diagonal called level- dependent threshold method. However, the final step of the process is to reconstruct the image from the approximation coefficients and the retained coefficients from the detail by applying the inverse of the DWT. The quality of the recovered image depends on the selected threshold value and the percentage of the total coefficients will be retained after thresholding. Hence, in this paper, two ways have been proposed to select the threshold value. In the first way a new successive – approximation threshold (*SA-thresh*) selection method has been proposed to choose the value of the global threshold, where the threshold values are chosen in equations (11) and (12) as follows:

$$T_i = (T_i - 1)/2 \tag{11}$$

And the initial thresholds T_0 is chosen as:

$$T_0 = \operatorname{int}(\max(C_i))/2 \tag{12}$$

This method takes the initial threshold in the first pass of thresholding the detail coefficients and then refines its value in the next pass and repeats this process until the quality of image that we need is gotten; this will permit us to observe the image quality after each pass of thresholding. The second way has been developed by applying the PSO algorithm to obtain the desired image quality through selecting a suitable threshold value for the image. The two suggested ways are shown in figure (3) as follows:

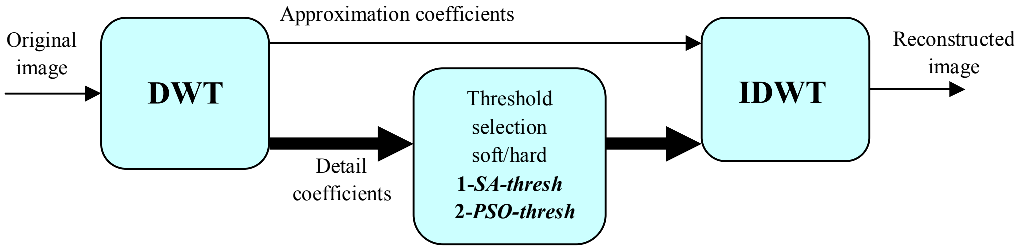


Figure (3): proposed model for threshold selection methods

5. Algorithm Steps and Simulation Results

A 256 x 256 grayscale version of the color image "wflower.jpeg" has been selected to test the two proposed models of image compression. A2-D "Haar" wavelet function is used for one-level decomposition of the image. Hard and Soft threshold methods have been used as basic techniques. The compression algorithm has been made by the following steps:

Step1: load the image into the MATLAB program and convert it into gray scale.
Step2: decompose the image into approximation and detail coefficients by DWT.
Step3: threshold the detail coefficients by methods that have been proposed above.
Step4: reconstruct the image from the approximation coefficients and the thresholded version of the detail coefficients by IDWT.
Step5: evaluate the PSNR, MSE and CR for the reconstructed image. Tables number (1), (2), (3) and (4) shows the simulation results of these objectives. However, the relationships of the PSNR, MSE and CR that are depended in our calculations written in equations (13), (14), and (15) as follows:

$$MSE = \frac{1}{MN}\sum_{x=0}^{M-1}\sum_{y=0}^{N-1}[f(x,y) - f'(x.y)]^2 \qquad (13)$$

$$PSNR = 10\log_{10}(255^2 / MSE) \qquad (14)$$

$$CR = \frac{number\ of\ zero\ coefficients\ after\ threshold}{number\ of\ all\ coefficients\ before\ threshold} \qquad (15)$$

PSO algorithm applied to the image, the swarm was considered equal to 10 , and the variable of the problem was considered equal to 1, and the values of w, c1,c2 were considered as default values as discussed in section(3).

To simplify the understanding of how the PSO algorithm worked with image compression scheme we present this process by flow chart as shown in figure (4). At first we should have a fitness function to be minimized to zero. However, if we choose our fitness function about the CR we will write it in equation (16) as follows:

$$f(T) = CR_{pso}(T) - CR_{given} \qquad (16)$$

Also, it can be written as follows:

$$f(T) = \frac{C - C^*(T)}{C} - CR_{given} \qquad (17)$$

Where C denotes to the number of overall coefficients before thresholding and C^* is the number of the retained coefficients which can be evaluated by using equations (9) and (10).

By this method, the algorithm of PSO will select the suitable value of threshold T that make the new CR_{pso} reaches the desired CR_{given} value making the objective function minimize to zero. In this way we can select the compression ratio that we need to compress the image to it. The same CR that we get from (SA-thresh method) selected as a given CR to the PSO algorithm so as to compare the performance between these methods. The same thing we can do if the fitness function has been taken about the PSNR.

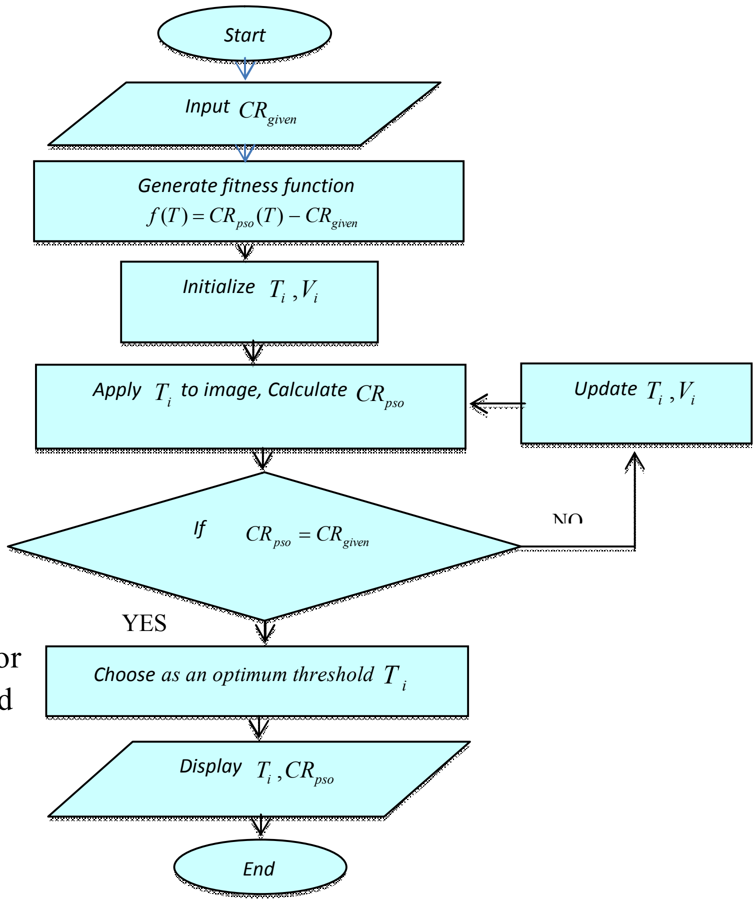


Figure (4): A PSO flow chart for selecting the optimum threshold value at a desired *CR*

Table 1: Simulation results for hard thresholding method using (SA-Thresh)

Threshold value $T_i = (T_i - 1)/2$	Mean square error MSE	Peak signal to noise ratio PSNR in dB	Compression ratio CR in %
97	239.1910	24.3434	74.5468
49	114.0707	27.5591	71.7621
25	42.2225	31.8754	65.8997
13	13.6126	36.7914	57.3685
7	4.1399	41.9609	47.4426
4	1.2529	47.1516	37.4817

Table 2: Simulation results for soft thresholding method using (SA-Thresh)

Threshold value $T_i = (T_i - 1)/2$	Mean square error MSE	Peak signal to noise ratio PSNR in dB	Compression ratio CR in %
97	281.6877	23.6331	74.5483
49	191.3734	25.3120	71.7804
25	98.6228	28.1910	65.9760
13	43.2474	31.7712	57.4646
7	17.5548	35.6868	47.6227
4	7.1889	39.5642	37.8998

Table 3: Simulation results for hard thresholding method using PSO

Given CR in % we need	Threshold value T obtained from PSO algorithm	New CR in % Obtained from PSO	Peak signal to noise ratio PSNR in dB	Mean square error MSE
74.5468	78.93	74.5010	25.1501	198.6403
71.7621	43.86	71.7033	28.2345	97.6404
65.8997	22.99	65.7921	32.4530	36.9639
57.3685	12.51	57.2899	36.9353	13.1690
47.4426	6.93	47.3937	42.2798	3.8468
37.4817	3.98	37.3985	47.3899	1.1860

Table 4: Simulation results for soft thresholding method using PSO

Given CR in % we need	Threshold value T obtained from PSO algorithm	New CR in % Obtained from PSO	Peak signal to noise ratio PSNR in dB	Mean square error MSE
74.5483	78.51	74.5120	23.9882	259.5708
71.7804	43.63	71.7152	25.7383	173.4802
65.9760	23.01	65.8947	28.6104	89.5442
57.4646	12.54	57.3924	31.9864	41.1564
47.6227	6.98	47.5851	35.7846	17.1639
37.8998	3.99	37.7731	39.5642	7.1889

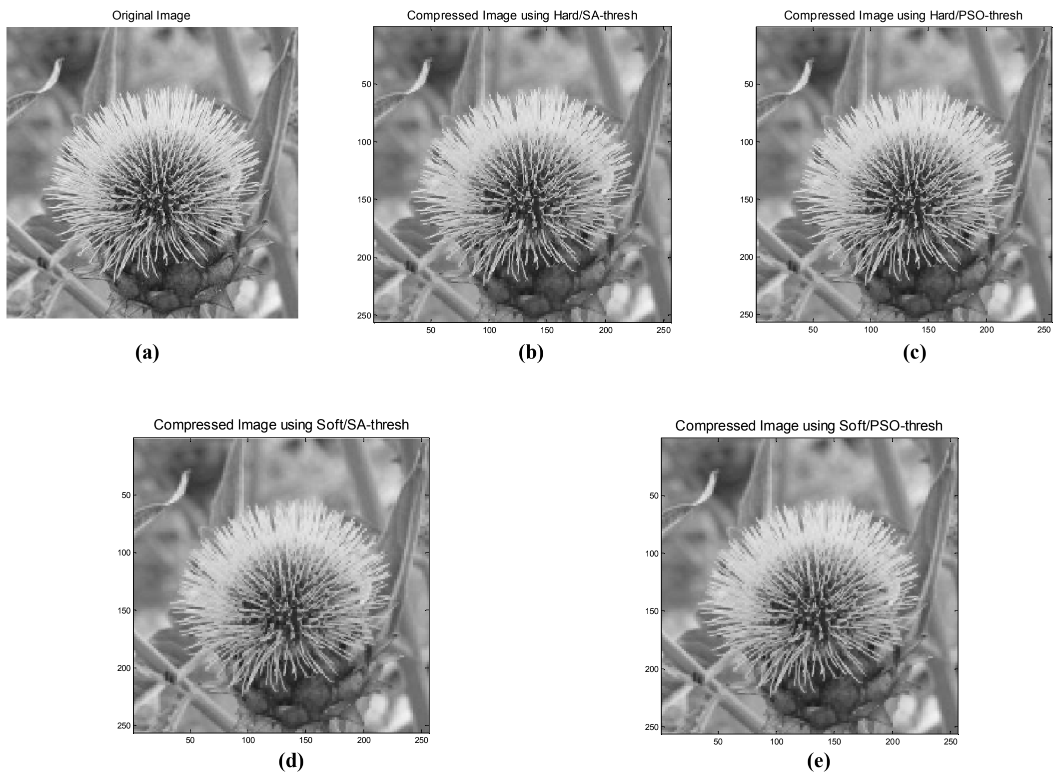


Figure (5): a) original image, b) compressed image using Hard/SA-thresh, c) compressed image Hard/PSO-thresh, d) compressed image using Soft/SA-thresh, d) compressed image using Soft/PSO-thresh, all with CR=47%

6. Conclusion

In this paper, we have developed two approaches for selecting the image quality that we need to store or transmit through the channel (SA-thresh and PSO-thresh). From the above results we conclude that the performance of the image compression system with PSO algorithm shows better results in the PSNR than that with using the (SA-thresh) method. The key notion here is that the PSO algorithm reaches the optimum value of threshold faster and with less value than that used in the (SA-thresh) method. Although, there is a small difference between the new CR_{pso} and the desired CR_{given}, we have gotten a good quality for the image with less mean square error (MSE). However, such a method is useful to automatically select the value of threshold for the image. And that gives us a hint about the possibility to adaptive transmission of the image via channel by selecting its size through compressing it into a desired ratio. This means we can control the size of bit stream that represents the image and would be transmitted through the channel. Therefore, in this case we can preserve the transmission rate of the channel. However, this paper used a one-level decomposition of DWT. It can be extended by using a multi- level decomposition or by using other types of wavelet basis function. Also, it can be used a hybrid optimization algorithm from PSO and other evolutionary algorithm such as IWO (Invasive Weed Optimization) algorithm to enhance the speed of selection threshold value *T*.

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