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Performance Analysis of Block PSO for Image De-noising using Wavelet Transform

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Abstract: *Image de-noising is one of the fundamental problems in the field of image processing needed for improving the image quality before performing different high-level vision tasks. Numerous wavelet based de-noising methods were utilized for performing image de-noising process. In such works, there is a lack of analysis in selecting the appropriate threshold value. Moreover, such analysis leads to the determination of static threshold value. The basic formulae exist if we treat noisy image as a single image without dividing it into blocks. We can also check the performance of the conventional methods by dividing the noisy image into different block sizes and then applying dynamic methods to choose proper threshold value. In this paper, we proposed an adaptive image de-noising technique by dividing the noisy image into blocks then applying wavelet transform on it and then by applying Particle Swarm Optimization (PSO) technique to select proper threshold values. The performance of the image de-noising technique is evaluated by comparing the result of proposed technique with the conventional soft thresholding technique in terms of peak signal-to-noise ratio (PSNR).*
Keywords: *Image De-noising, wavelet Decomposition, Particle Swarm Optimization (PSO), Adaptive Thresholding*

I. Introduction

Mostly every sort of data includes some noise. Noise reduction is one of the essential steps for all complicated algorithms in computer vision and image processing. This problem has continued for a long time and still there is no proper solution for solving it. Over the last decades, there has been shown a great interest to tackle the problem related to noise removal in signals and images. Most of the natural images are assumed to have additive random noise, which is modeled as Gaussian type. Speckle noise is observed in ultrasound images, whereas Rician noise affects MRI images [1]. Removing the noise from an image is a field of engineering that deals with the methods used to recover an original scene from degraded observations. It is an area that has been explored extensively in the image processing, astronomical, and optics communities for some time. Image de-noising plays a significant role in image pre-processing [8]. Image de-noising is used to remove the noise from a noisy image corrupted during acquisition and transmission. Image de-noising is performed to eliminate the additive noise while preserving the vital signal features. Thus, de-noising is often a necessary and the first step to be considered before the image data is analyzed. It is necessary to apply an efficient de-noising technique to compensate for any data corruption. The image de-noising methods are usually categorized as spatial domain methods or transform domain methods. The transform domain methods convert an image from the spatial domain into wavelet domain or frequency domain and suppress noise in the transform domain. But in the case of spatial domain methods, the noise is suppressed within the spatial domain.

Many different approaches such as spatial adaptive filters, wiener filter, wavelet thresholding, anisotropic filtering, bilateral filtering, total variation method, non-local methods of morphological analysis, transform domain methods and some more are already studied to remove the noise from images [9]. Among these techniques, wavelet thresholding has been reported to be a highly successful method [2]. In recent years, there has been a lot of research on wavelet thresholding and threshold selection for signal and image de-noising, because wavelet provides an appropriate basis to separate noisy signal from image signal. In many hundreds of papers published in journals throughout the scientific and engineering disciplines, a large number of wavelet-based tools and ideas were proposed and studied [3]. Wavelet based methods have always been a good choice for image de-noising. Wavelet transforms are successfully used in many different scientific fields such as image compression, image de-noising, signal processing, computer graphics, and pattern recognition. The wavelet de-noising scheme using soft thresholding and hard thresholding appears to be a good choice for a number of applications [10]. In wavelet thresholding, a signal is decomposed into different approximation (low-frequency) and detail (high-frequency) sub bands, and the coefficients in the detail sub bands are processed via hard or soft thresholding. As the application areas related to image de-noising are more, there is a big demand for efficient de-noising algorithms.

A handful of research works available in the literature deals about the removal of noise in the images using wavelet transformation. A few of the most recent literature works in this topic are reviewed in this section. Kother Mohideen et al [4]. have proposed a multi-wavelet method to suppress the noise and to make some enhancement in digital mammographic images. Here, the image has been preprocessed to make some improvements in its local contrast and discriminations of subtle details. Image suppression and edge enhancement have been performed based on the multi-wavelet transform. At each resolution, coefficient associated with the noise has been modeled and generalized by Laplacian random variables. Multi-wavelet satisfies both symmetry and asymmetry, which are very important characteristics in Digital image processing. The better de-noising result depends on the degree of the noise, generally its energy distributed over low frequency band while both its noise and details have been distributed over high frequency band and also applied hard threshold in different scale of frequency sub-bands to limit the image. The intention of their research was to indicate the suitability of different wavelets and multi-wavelet on the neighborhood in the performance of image de-noising algorithms in terms of PSNR. Finally, the wavelet and multi-wavelet techniques have been compared to produce the best de-noised mammographic image using efficient multi-wavelet algorithm with hard threshold based on the performance of image de-noising algorithm in terms of PSNR values.

Chinna Rao et al [5].have introduced a reconfigurable adaptive threshold estimation method to remove noise from images in the wavelet domain on the basis of the Generalized Gaussian distribution (GGD) modeling of sub-band coefficients. Their proposed method called Regular-Shrink was computationally more efficient and adaptive because the parameters required for estimating the threshold depends on sub-band data. Edge information is the most important high frequency information of an image, so it is necessary to maintain more edge information while de-noising. In order to preserve image details as well as for canceling image noise, they have presented an image de-noising method: image de-noising based on edge detection. Before de-noising, image's edges have been detected first, and then the noised image has been divided into two parts: edge part and smooth part. Therefore, high de-noising threshold has been assigned to smooth part of the image and low de-noising threshold to edge part. The theoretical analyzes and experimental results have shown that, when compared to commonly used wavelet threshold de-noising methods, their proposed algorithm has the ability to maintain edge information of an image, as well as it can improve the signal-to-noise ratio of the de-noised image.

In this work, a heuristic image de-noising technique is proposed to find the best possible solution for the different noisy images. The proposed technique is based on adaptive wavelet thresholding , we proposed an adaptive image de-noising technique by dividing the noisy image into blocks of different sizes and then applying wavelet transform on it and then by applying Particle Swarm Optimization(PSO) algorithm to select proper threshold value. The threshold value is computed dynamically for different block sizes and the performance of the system is analyzed. The rest of the paper is organized as follows: Section II reviews the related works with respect to the proposed method. Section III presents the proposed heuristic technique. Section IV discusses about the implementation results and section V concludes the paper.

II. Wavelet Theory

A wavelet is a waveform of limited duration that has an average value of zero. Wavelet transforms allow us variable size windows. Wavelet transforms are exciting because they too are comparisons, but instead of correlating with various stretched, constant frequency sinusoid waves they use smaller or shorter waveforms known as wavelets that can start and stop. We can use long time intervals for more precise low frequency information and shorter intervals for the higher frequencies. The wavelet transform (WT) has gained wide spread acceptance in image de-noising because of its inherent multi-resolution property.

Discrete Wavelet Transform (DWT) [6]

The output of discrete wavelet coefficients of a function being expanded is a sequence of numbers like samples of a continuous function and the resulting transform is called the discrete wavelet transform (DWT). The DWT transform pair is given below

$$W_{\varphi}(j_0,k)=\frac{1}{\sqrt{M}}\sum_{x} f(x)\varphi_{j0,k}(x) \tag{1}$$

$$W_{\psi}(j,k)=\frac{1}{\sqrt{M}}\sum_{x} f(x)\psi_{j,k}(x) \tag{2}$$

For $j \geq j_0$ and $f(x)=\frac{1}{\sqrt{M}}W_{\varphi}(j0,k)\varphi_{j0,k}+\frac{1}{\sqrt{M}}\sum_{j=j0}^{\infty}\sum_{k}W_{\psi}(j,k)\psi_{j,k}(x)$ (3)

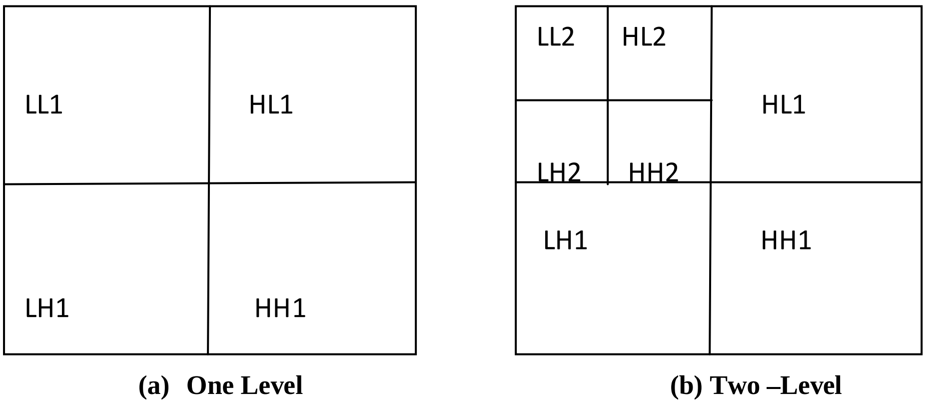
Here, $f(x), \varphi_{j0,k}(x), \psi_{j,k}(x)$ are functions of the discrete variables $x = 0,1,2,3,...M-1$. For example, $f(x) = f(x_0 + x\Delta x)$ for some $x_0, \Delta x$ and $x = 0,1,2,3,...M-1$. Normally, we let $j0 = 0$ and select M to be a power of 2 so that the summations are performed over $x = 0,1,2,3,...M-1$, $j = 0,1,2,3,...J-1$ and $K = 0,1,2,3,...2^j - 1$. The one dimensional transform in the above cab be extended to two-dimensional transform. The two-dimensional DWT can be obtained by using (4)

$$f(x,y) = \frac{1}{\sqrt{MN}} \sum_m \sum_n W_\varphi(j_0, m, n) \varphi_{j0,m,n}(x,y) + \frac{1}{\sqrt{MN}} \sum_{i=H,V,D} \sum_{j=j_0}^{\infty} \sum_m \sum_n W_\psi^i(j,m,n) \psi_{j,m,n}^i(x,y) \tag{4}$$

Where, $W_\kappa(j_0, m, n) = \frac{1}{\sqrt{MN}} \sum_{x=0}^{M-1} \sum_{y=0}^{N-1} f(x,y) \varphi_{j0,m,n}(x,y)$ and

$$W_\psi(j,m,n) = \frac{1}{\sqrt{MN}} \sum_{x=0}^{M-1} \sum_{y=0}^{N-1} f(x,y) \psi_{j,m,n}^i(x,y) \quad i = \{H, V, D\}$$

The DWT is identical to a hierarchical sub band system where the sub bands are logarithmically spaced in frequency and represent octave decomposition. The one dimensional filter in (4), (5) can be used as two dimensional separable filters for the processing of images. A separable filter are first applied vertical dimension and then horizontal dimension and then down sampling is performed in two stages once before the second filtering operation to reduce the overall number of computations which is shown in Fig. 1(a). The resulting filtered output denoted LL1, LH1, HL1 and HH1 represent the finest scale wavelet coefficients and LL1 corresponds to coarse level of wavelet coefficients. To obtain the next level of wavelet coefficients, the sub band LL1 alone decomposed into LL2, HL2, LH2, and HH2. This results in two level wavelet decomposition as shown in Fig. 1(b).



(a) One Level **(b) Two –Level**

Fig. 1 Image decomposition

III. Particle Swarm Optimization

PSO is an evolutionary algorithm to simulate the movement of flock of birds. Meta heuristic algorithms for engineering opti-mization include genetic algorithms (GA), simulated annealing (SA), variants of particle swarm optimization (PSO), ant colony algorithm, bee algorithm, harmony search (HS), firefly algorithm (FA), and many others. Particle swarm optimization (PSO) was developed by Kennedy and Eberhart in 1995, based on swarm behavior such as fish and bird schooling in nature. Like other population-based search algorithms, PSO is initialized with a swarm of random solutions (particles). Each particle flies in D-dimensional problem space with a velocity, which is adjusted at each time step. The particle flies towards a position, which depends on its own past best position and the position of the best of its neighbors. The quality of a particle position depends on choosing the objective (fitness) function. The position of the i th particle is presented by a vector $X_i = (x_{i1}, ..., x_{id}, ..., x_{iD})$, where $x_{id} \in [x_{\min,d}, x_{\max,d}], d = 1, ..., D. x_{\min}$ and $x_{\max,d}$ are the lower and upper bounds for the d th dimension, respectively. The best position of particle i is recorded as $P_i = (p_{i1}, ..., p_{id}, ..., p_{iD})$ is called $pbest$. Similarly, the location of the best particle among the population is recorded by the index g and the location P_g is called $gbest$. The velocity of the i th particle $V_i = (v_{i1},...,v_{id},...,v_{iD})$, is limited to a maximum velocity $V_{\max} = (v_{\max,1},...,v_{\max,d},...,v_{\max,D})$. At each time step, the particles velocity and positions are updated depending on their $pbest$ and $gbest$ according to (5) and (6)

$$v_{id}^{t+1} = wv_{id}^t + c_1 r_1 (p_{id}^t - x_{id}^t) + c_2 r_2 (p_{gd}^t - x_{id}^t) \quad (5)$$

$$x_i^{t+1} = x_i^t + v_i^{t+1} \quad (6)$$

Here w is the inertia weight determining how much of the previous velocity of the particle is preserved, r_1 and r_2 are two uniform random numbers samples from $U(0,1)$. c_1 is a positive constant, called as coefficient of the self-recognition component, c_2 is a positive constant, called as coefficient of the social component and the choice of value is $c_1 = c_2 = 2$ generally referred to as learning factors. For the velocity update equation, the second part represents the private thinking by itself, the third part is the social part, which represents the cooperation among the individuals.

Algorithm of PSO: Pseudo code of the PSO algorithm is shown below [7]

Objective Function $f(x), x = (x_1,....,x_p)^T$

Initialize locations x_i and velocity v_i of n particles

Find g^* from min $\{f(x_1),..., f(x_n)\}$ $(at\ t = 0)$

While (criterion)

$t = t + 1$ (Pseudo time or iteration counter)

for loop over all n particles and all p dimensions

Generate new velocity v_i^{t+1} using equation ()

Calculate new locations $x_i^{t+1} = x_i^t + v_i^{t+1}$

Evaluate objective functions at new locations x_i^{t+1}

Find the current best for each particle x_i^*

end for

Find the current global best g^*

end while

output the final results x_i^* and g^*

Fig. 2 Pseudo code for particle swarm optimization

IV. Experimental Setup And Results

Two gray level images, "Lena.jpg" and "House.jpg", of size 256x256 are used as benchmark images to evaluate the performance of block PSO for image de-noising using wavelet transform. The experimental setup is shown in Fig. 2. The performance of the developed system is analyzed using $db8$ wavelet transform.

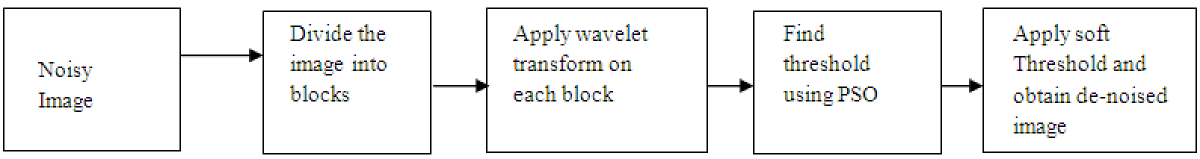


Fig. 3 Block PSO for image de-noising using wavelet transform

Experimental setup in steps

Step 1: Obtain noisy image of size 256x256

Step 2: Consider the noisy image in step 1as a single block.

Step 3: Initialize PSO algorithm with population size n=20, c1=1.8 and c2=1.8 and w=0.1

Step 4: Initialize particle position and velocity with dimension one and considered this as the threshold value for the given problem.

Step 5: Apply DWT on the noisy image to obtain LL1, LH1, HL1and HH1 wavelet coefficients.
Step 6: Soft threshold LH1, HL1 and HH1 wavelet coefficients using (7) without modifying LL1.
Step 7: Inverse DWT is applied on LL1, LH1, HL1 and HH1 to obtained de-noised image.
Step 8: Calculate fitness value PSNR using the formula (8) and (9) between original image and de-noised image of each and every particles in the algorithm.
Step 9: Maximization of PSNR value is considered for the given problem so that $pbest$ and $gbest$ are calculated
Step 10: Update velocity equation using the formula (5)
Step 11: Update position equation using the formula (6)
Step 12: Repeat step 5-11 for the given number of iterations.
Step 13: Repeat steps 1-12 by changing values in step2 by dividing the given noisy image into 4, 16 and 64 blocks.
Step 14: Compare the results.

Threshold value calculation (λ):

1. Calculate a wavelet transform to obtain LL, LH, HL and HH coefficients. The noise threshold will be calculated on the highest frequency coefficient spectrum HH.
2. Calculate the median absolute deviation δ_{mad} on the largest coefficient spectrum. The median is calculated from the absolute value of the coefficients. The equation for the median absolute deviation shown below:

$$\delta_{mad} = \frac{median(median(|HH|)}{0.6745}$$

3. Calculate noise threshold λ using the equation below

$$\lambda = \delta_{mad}\sqrt{2\log(N)}$$

Where N is the number of pixels in the sub image, i.e., HL, LH or HH.

Soft Thresholding (d_{ik}^{soft}):

Soft thresholding sets any coefficients less than or equal to the threshold to zero. The threshold is subtracted from any coefficient that is greater than the threshold. This moves the image coefficients toward zero.

$$d_{ik}^{soft} = \begin{pmatrix} sign(d_{ik})(|d_{ik} - \lambda|) & for\,|d_{ik}| > \lambda \\ 0 & for\, d_{ik} \le \lambda \end{pmatrix} \tag{7}$$

$$PSNR = 10\log_{10}(255^2 / MSE) \tag{8}$$

$$MSE = \frac{1}{MN}\sum_{x=0}^{M-1}\sum_{y=0}^{N-1}[f(x,y) - f^{'}(x,y)]^2 \tag{9}$$

where $f(x,y)$ and $f^{'}(x,y)$ are original image and threshold images of size MxN respectively.

Table 1: Experiment results threshold value and PSNR for the given compression ratio on "Lena" image.

S.No	Noise Variance	PSNR in dB Using Soft Thresholding Block size 256x256	PSNR in dB using PSO			
			Block size 256x256	Block size 1286x128	Block size 64x64	Block size 32x32
1	5	37.30348	37.6445	37.6624	37.68402	37.53758
2	10	31.20306	31.24129	31.3683	31.46049	31.15827
3	15	28.26199	28.43689	28.49906	28.51279	28.35377
4	20	26.57327	26.66842	26.66842	26.69563	26.57469
5	25	25.17195	25.20176	25.20176	25.21774	25.08784
6	30	23.91028	23.9135	23.9135	23.92057	23.81176

Table 2: Experiment results threshold value and PSNR for the given compression ratio on "House" image.

S.No	Noise Variance	PSNR in dB Using Soft Thresholding Block size 256x256	PSNR in dB using PSO Block size 256x256	Block size 128x128	Block size 64x64	Block size 32x32
1	5	37.65152	37.73792	37.74472	37.75008	37.10872
2	10	31.56201	31.56927	31.57744	31.59773	31.53007
3	15	28.68862	28.77331	28.77693	28.78246	28.71784
4	20	26.76302	26.82448	26.82861	26.82901	26.77033
5	25	25.26958	25.30675	25.30686	25.30863	25.26443
6	30	23.98638	23.99832	24.00799	24.01339	23.92776

V. Conclusion

Block PSO with maximizing fitness PSNR value is implemented to find the threshold values for different block sizes. From the above results we can conclude that PSNR is increasing when block sizes reduced from 256x256 to 64x64. Again PSNR value is decreasing from block size 32x32. So we can conclude that the best block size for de-noising of images using soft thresholding is 64x64.This paper can be extended by using different variants of PSO, different wavelets and also using 2 level wavelet decompositions.

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