A Novel Approach for Image Denoising and Performance Analysis using SGO and APSO

V MNSSVKR Gupta¹, KVSS Murthy², R Shiva Shankar³

¹,³Computer Science and Engineering Department, ¹,² S.R.K.R. Engineering College, Bhimavaram, West Godavari, Andhra Pradesh, India

guptavkrao@gmail.com; kvssrmurthy75@gmail.com; shiva.srkr@gmail.com;

Abstract. Image denoising is essential to extract the information contained in an image without errors. A technique of using both wavelets and evolutionary computing tools is proposed to denoise and to improve the image quality. An adaptive thresholding-based wavelet denoising technique in the threshold function is coordinated by novel social group optimization (SGO) and accelerated particle swarm optimization (APSO) is proposed. The simulation oriented experimentation is taken out employing MATLAB and the analysis is carried out using the image property metrics similar to peak signal to noise ratio (PSNR), mean square error (MSE) and other structural similarity index metrics (SSIM).

1. Introduction

With the latest advances in wireless communication the exchange of information over large bandwidth channels has increased. In the modern world the transmission of image from security cameras, Closed circuit cameras, Patient or baby monitoring systems and several general, Civil and commercial applications is possible [1]. In all these examples mostly, the channel is wireless and noisy. As a result, the information contained in the image may be adulterated. In general, the noise can be additive and in some cases it is multiplicative. Due to the random and non-linear behaviour of the noise, the adulterated image with noise loses its quality and valuable information is also lost. To enhance the image quality it is required to separate the noise from the image. This process is known as Image denoising. Several spatial and transform domain-based techniques are employed to denoising the image and enhance its quality [2]. However, all these techniques provide local solutions as they can be easily trapped in local optima. Hence, they can only provide local optima’s and cannot provide desired and global solutions. However, throughout many medical image applications, the methods used to increase resolution and qualities of noisy images remain a problem. One of the primary challenges in medical imaging research is removing noise from digital images [3]. The restoration model can be formulated as an inverse problem, meaning that it could be approached by solving a related nonlinear problem [4]. Image reconstruction is the process of estimating the original image from corrupted data. The ability to view and analyze remote sensing images is aided by restoration. The blur effect of an image was reduced during restoration [5]. As a result, restoration techniques are geared toward modelling deterioration and using the inverse method to restore the original image. The aim of denoising is to efficiently eliminate noise while retaining as many of the input images information as possible. Many methods to removing noise have already been suggested so far [6]. In the recent days, novel evolutionary computing tools are used to obtain excellent solutions to several engineering problems. Hence, it is possible to implement the evolutionary computing techniques (ECT) for an efficient denoising of image and separate the image from the noise. Considering this, the novel
population based, Social Group Optimization Algorithm (SGOA) is used as ECT along with wavelet thresholding function for image demising [7].

2. Literature Survey
R S Shankar et al. [8] majorly concentrated on noise reduction in pgm images and applied object oriented fuzzy filter on image data. Image data undergoes fuzzy derivative estimation technique for identification of edges and fuzzy smoothing performed by previous pixel knowledge for correction term of pixel value. The k values are calculated by applying fuzzy smoothing technique over 15 iterations and compared with mean filter, median filter methods. Patrick Perez et al. [9] concentrated mainly on poison image editing tools for editing image regions in a continuous manner. The first set of features helps with the transparent importation of both transparent and explicit source image regions into a destination environment, while the second set of tools focuses on mathematical principles for image adjustment, such as how the texture, colour, and size of objects in a selected region affects the texture, colour, and size of objects. The editing options by this method ranges from mixing with other source image region to alterations like texture, colour, illumination etc and stated these can be further increased with advancements.

Wilbur C.K. Wong and Chung A. C [10] mainly focuses on noise reduction techniques in 2D,3D medical images and proposed a Nonlinear, non iterative method (TF) that uses a small spatial window and only needs one iteration to reduce the noise of image. CNR metrics for GF, BF and TF are noted as 17.64, 17.25, 18.45 and other metrics CNR with WM, GM are also calculated and compared. Stated that this model helps in efficient noise reduction and smoothing without over smoothing the edges of images, as compared to others. R S Shankar et al. [11] presented Convolution neural network model for greyscale image colourization. Feature extractor helps in extracting the features and pre-trained model Inception ResNet V2 (by google) is used for feature extractor in this model. Encoder output and features are combined at fusion layer and sent decoder to process the required output. Model is initialized different parameters like batch size, epoch, steps for epoch as 10, 100, 1000 and epoch with least error rate is said to be best for greyscale colorization. This model noted to have more efficiency in colouring, processing, accuracy, performance and less in complexity.

D Van De Ville et al. [12] proposed fuzzy filtering technique for noise reduction in images. The images is passed through 2 stages fuzzy derivative stage for eight unique directions identification of pixel and smoothing by calculating contribution of neighbouring pixels by fuzzy rules which make use of membership functions. The model is tested on different images of boats images, cameraman images with changing alpha values like 1.0, 2.0, and 3.0 and compared with other filtering techniques like MIFC, EIFC, IFC, FM etc. Main feature of the model is to distinguish between the local variations due to noise, image structures and can compete with cutting-edge filtering techniques. R S Shankar et al. [13] applied Convolution neural network on image data for sharpening blur images. CNN proposed model uses ResBlocks and takes the input of blur images of different resolutions that are down sampled at encoder. Feature map helps in generating latent sharp image at every stage and final output is converted to required format at decoder. Data of 5 images are tested using this model and epoch is changed slowly from 1 to 100 to observe changes. PSNR, SSIM metrics of model are noted to be 30.10, 0.932 better than other models like lstm, gru.

Raman Maini and Himanshu Aggarwal [14] highlighted the issue of speckle noise effect on medical diagnosis and compared different speckle noise reduction techniques mean filter, median filter, local region filter, frost filter and diffusion filter. The image with 227x167 pixels with sharp edges is used for experiment. Metrics MSE, SNR, visual quality of image are used for comparing the models and stated that diffusion filter with nonlinear nature and adaptive anisotropy. A Abdelhamed et al. [15] mainly focused on issue of denoising the high quality images from smart phones and applied CNN based methods on dataset. The dataset consists of 30,000 noisy photographs taken with 5 smart phones within 10 scenarios under different illumination conditions, which were used to create ground truth images. Metrics PSNR, SSIM, TIME are calculated for different models BM3D, KSVD, LPPPCA, WNNM, MLP, TNRD and DnCNN are stated CNN based methods outperforms patch based methods. Shi Guo et al. [16] implemented a CBDNet on the noisy and real image pair’s data. The data was collected from Nam dataset and DND benchmark. To train the model usage of Photographs that are
noisy in real life and their almost noise-free equivalents are included. To address underestimation of noise level, a noise estimation subnetwork with asymmetric learning is used, but it is related to the CBDNet to correct denoising performance. PNSR values 38.06, 41.31 and SSIM values 0.94, 0.97 on two datasets are noted. They concluded that combining both synthetic and real noisy images in training can improve a network’s denoising efficiency. Stamatios Lefkimmiatis [17] proposed Convolution Neural Network based on non-local image model for denoising in grayscale and colour images. Non-local processing with discriminative learning as an advantage which is performed on the image data taken from Berkeley segmentation dataset. NLNet5 model on grayscale outperforms other models with 31.52, 29.04, 26.07, same like CNLNet5 model on colour image gave 33.6, 30.96, 27.64 PSNR values on different STD noise values. Concludes that with this the image restoration and denoising image is so efficient than other state-of-the-arts models without involving extra cost also used for future advancements. Chunwei Tian et al. [18] raised the issue of weak shallow layers on deep layers in some deep CNN and proposed attention-guided denoising CNN (ADNet). Integrated with sparse block for balancing output and efficiency by removing noise with dilated or common convolutions, reconstruction block (RB) denoising the image, FEB for combining global and local features. The average PSNR values on BSD68 are noted as 31.7, 29.2, 26.2 on different image sets. For synthetic noisy images, real noisy images, and blind denoising, experimental results show that the proposed model ADNet is very successful in both quantitative and qualitative evaluations. Yingkun Hou et al. [19] discussed issues of patch level NSS prior and proposed a pixel level NSS prior for finding similarity of pixels across the non-local region for denoising the real time images and enhancing performance. Blind image noising is developed by lifting Haar transform and Wiener filtering techniques. The internal steps of Two-Stage Denoising Framework, Complexity Analysis, and Extension to Real-World Image Denoising are performed on the benchmark dataset. Evaluation metrics PSNR and SSIM averages are noted 38.8, 0.95. And out performs all other deep methods.

3. Problem Statement
The general procedure of wavelet based denoising follows several steps. The first step involves in transformation of image into wavelet domain. The number of levels of decomposition depends on complexity of the problem and the type of noise included into image. In general, two-level decomposition is sufficient for a Gaussian noise induced images. In the wavelet domain, the threshold value is determined or estimated. Later, the threshold is applied to the entire matrix of the image. Further, as a next step, the transformed and threshold image is compared with the other segments of decomposed image and subjected to inverse wavelet transformation. This yields a denoised image. The thresholding technique can be hard thresholding or soft thresholding. However, the literature suggests adaptive thresholding which uses threshold levels as determined by an algorithm. The thresholding phenomenon is described as Shrinkage in wavelets. For denoising images, the suggested wavelets shrinkages are Visu Shrink (Universal), SURE shrink (Adaptive) and Bayes (Adaptive). In this work, the adaptive shrinkage technique based non-uniform threshold is used. The non-uniformness of the threshold distribution is function of a set of tuning parameters. Determining the set of tuning parameters which produce the highest PSNR and lowest MSE can be considered as the problem statement.

In this work, both SGOA and APSO are used to optimize the design parameters in order to denoise the images. The performance of the algorithm can be evaluated using several optimization parameters like convergence, computational time and optimal solution produced in terms of PSNR and MSE. However, in this work, the evaluation is carried out in terms of the image quality metrics only. The fitness function is given as:

\[
\text{Optimum Value} = \min \{f(I_m)\} \quad (m=1)^M
\]

Here, \(I\) is an individual while \(M\) refers to the number of individuals. The expression \(f(I)\) corresponds to the fitness value of individual. Every individual is a set of tuning parameters of the threshold function using which the corresponding denoised image is reconstructed and further the image quality metrics is computed in terms of PSNR. The highest PSNR in the population is considered as the best optimal for that iteration.
4. Proposed Methodology

In this study, two evolutionary computational algorithms namely SGOA and APSO are applied to denoising problem in gray scale images. For image denoising, linear filters are also ineffective against signal based noises. Similarly, image denoising algorithms based on spatial frequency filtering and wavelet transforms take a long time to create and are computationally complex. Image denoising and accuracy can be improved with increased efficiency if all of the above shortcomings in literary works are tackled. The proposed method distinguishes between noisy and noise-free pixels in the image, despite smoothing the data for filtering. After that, the noise-free image is created using the filtering window. In this Section, a brief description of the algorithms and their implementation are discussed and shown a structure of proposed methodology in figure 1.

![Figure 1: Structure for Image Denoising using APSO and SGOA](image)

**SGOA**

It was created by simulating human community behaviour and information transfer practices. The SGO algorithm consists of objective function and acquiring the agents to find the best possible solution to the problem at hand. The motivation for SGOA is the response of individual living in the community. People reach over several difficulties some are manageable and often are complicated obstacles in their everyday life. These problems are mostly non-linear. SGOA was inspired by the behavioural model and information coefficient of people in overcoming their daily life problems, as are most optimization approaches.

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**Algorithm 1: Standard Social Group Optimization Algorithm**

Start

- **Assume** five agents \( i = 1, 2, 3, 4, 5 \)
- **Assign** these agents to find the \( G_{best} \) in a \( D \)-dimensional search space
- **Randomly** distribute the entire agents in the group throughout the search space during initialization process
- **Compute** the fitness value based on the problem under concern
- **Update** the orientation of agents using \( G_{best} = \max \{ f(J_i) \} \)
- **Initialize** the improving phase to update the knowledge of other agents in order to reach the \( G_{best} \)
- **Initialize** the acquiring phase to further update the knowledge of agents by randomly choosing the agents with best fitness value
- **Repeat** the procedure till the entire agents move toward the best possible position in the \( D \)-dimensional search space
- **If** all the agents have approximately similar fitness values (\( G_{best} \))

Then

- **Terminate** the search and display the optimized result for the chosen problem

Else

- **Repeat** the previous steps

End

Stop
People in the group usually respond to complex obstacles by banding together as an organisation and transferring the possible solution among the organization's members, rather than solving the problem individually. As a result, a high degree of information coefficient is needed for information distribution between groups of people. In resolving obstacles, people hold information coefficient which is inspired by the behavioural model of people similar to truthfulness, group achievement etc which are real patterns. Knowledge distribution for determining a complicated non-linear difficulty in society can be examined in two steps. The transfer of knowledge among the people of the same organisation is treated as local influence. Similarly, global influence is treated as the exchange taking place between the individuals of different groups.

The aim of SGOA is to solve engineering problems that are often non-linear by posing a non-linear challenge as a common problem and solving it by sharing personal and community knowledge. Each individual has a unique information coefficient for resolving problems. As a result, each person is a viable option. A society or association is formed by such a group of people. Since each person's information coefficient determines how well he or she can solve a problem, they have a certain capacity to resolve a problem's resolution. This approach can be used to assess a person's health ability. The improvement process and the skills rehabilitation phase are the two phases of SGOA.

APSO

The APSO algorithm is a scaled version of the PSO in which the search capability is enhanced. The improved search capability allows the user to switch between the local search and global search with prior weightage on the desired search phenomenon. The literature suggests that the impact of global search is more on the solution search capability of an algorithm. In this APSO, the solution searching majorly takes place through the global search methodology. Accordingly, in every iteration the fitness of the individual is compared with only the global best. This is unlike the general case of PSO in which the position updating takes place in concern with the both the personal best and the global best. This technique yielded better results than simple PSO and frame work of APSO was shown in figure 2.

![General Frame work of APSO](image)

5. Results and Discussion

In this paper, implemented denoising of natural images using Accelerated PSO (APSO) and Social Group Optimization (SGOA) and analyzed their performance based on few image metrics. Different input images like Cameraman, Leena and Barbara are considered for the simulation experimentation which is shown in Figure 3. These images are induced with Gaussian noise for simulation purpose which are as shown in Figure 4 and denoised images after using APSO and SGOA are as shown in Figure 5 and the results were obtained for one more image and after denoising was shown in Figure 6.
Fig 3 - Input images of cameraman, Leena and Barbara respectively

Fig 4 - Input images after adding noise

Fig 5 - Enhanced images after denoising using SGOA

Fig 6 - Results obtained after Denoising
Table 1- Comparison of performance between APSO and SGOA

| Metrics | APSO | SGOA |
|---------|------|------|
|         | MSE  | PSNR | MSSIM | MSE  | PSNR | MSSIM |
| Cameraman | 49.674 | 31.182 | 0.994 | 35.7502 | 33.2323 | 0.996 |
| Barbara  | 49.371 | 31.224 | 0.994 | 35.8001 | 33.8520 | 0.996 |
| Leena    | 43.273 | 31.778 | 0.994 | 30.0083 | 33.3584 | 0.996 |

Different image quality metrics are considered like PSNR, MSE and SSIM are used to compare the input image and the denoised images was shown in Figure 7 and Figure 8. It is also possible to compare the performance of the algorithms with reference to resultant image metrics. Table 1 shows comparison results between APSO and SGOA. From the tabulated data it possible to state that the SGOA out performed in denoising of digital images when compared to APSO. The comparison and the performance analysis are carried out using only the image metrics and the output image quality. However, it is possible to compare the algorithm characteristics like computational time and convergence behaviour. The dominance of the SGOA is due to the structure of the algorithm in which the strategy adopts both the local search and global search. The PSNR in the case of cameraman image reported to be 31.182 dB using APSO which is 2dB less than the PSNR reported by the SGOA. Similarly, the SGOA consistently produced better results than the APSO in case of Leena and Barbara images.

Fig 7. Performance of Accelerated Particle Swarm Optimization (APSO).

Fig 8. Performance of Social Group Optimization Algorithm (SGOA).
6. Conclusion

Pertaining to the above results we can conclude that Social Group Optimization Algorithm out performed Accelerated PSO. Analysis for comparison is carried out with experimentation on different natural gray scale images and using different image quality metrics.

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