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Optimization of Image Denoising Filters Using Harmony Search - An Experimental Analysis

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Abstract: Edge preserving image denoising is a challenging task as noise level increases and still many algorithms are being proposed which works under various scenarios. The performance of the denoising algorithms gradually reduces, as the additive noise which corrupts the image increases. Thus the denoised image will lose its edges after removing the noise pixels and certainly the edge pixels should be preserved to have good image quality. In this paper, the authors aim at optimizing image filters using Harmony Search (HS) which can effectively eliminate impulse noise from the corrupted image. The proposed method is verified with standard image quality metrics like mean square error (MSE) and peak signal-to-noise ratio (PSNR) for various test images.

Key words: Impulse Noise · Denoising · Harmony Search · Optimization

INTRODUCTION

Random valued impulse noise occurs in the imaging system due to the corrupted pixels in the camera or during the transmission of pixel data. Many linear and non-linear image filters are proposed which improves the image quality by estimating the pixel values of the corrupted one [1-5]. To have a good performance of denoising algorithm, the noise level has to be estimated earlier to applying the noise removal technique. So far, median filter took the centre stage in the design of such nonlinear filter for removing impulse noise because of its good denoising power [1] and computational efficiency. However, it is not effective on images of higher noise density that results in significant information loss. The different variant of switching median filter that have been proposed like the adaptive median filter [5], the multistate median filter. These switching filters first locate the corrupted pixel and then replace them by using the local variant leaving other pixels unchanged.

There are many nature inspired optimization algorithms which follows the natural phenomena and works more efficiently by overcoming the existing limitations in the conventional methods. HS proposed by Geen [6, 7] was used for optimization of water distribution and it has gained its momentum in many engineering optimization problems. HS works for improving the music by searching better harmony. The steps involved in HS algorithm is shown in figure 1. It is worthwhile to employ HS for image denoising and to optimize the filter structures based in the noise level which should work even for highly corrupted images preserving the edges.

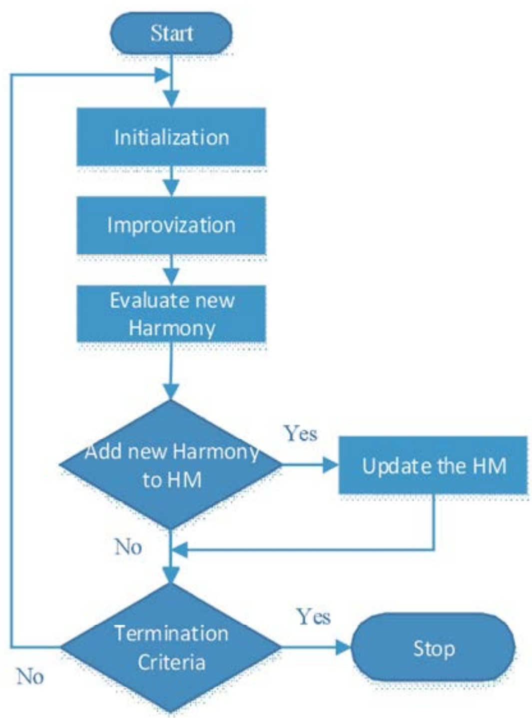

Fig. 1: Flow chart of HS

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Harmony Search: The performance of the HS algorithm primarily depends on the harmony memory which exploits the solution search space. Hence sufficient harmony memory needs to be initialized to make the random selection operator explore the complete search space [8]. The efficiency of the HS algorithm in solving multimodal problems is limited as the sub-optimal solutions will obstruct the harmony memory to move towards optimal solution and perhaps the HS algorithm sometimes suffers from stagnation during the search for optimal solution. Thus the HS is modified to dynamic regional harmony search (DRHS) algorithm which includes opposition-based learning [8, 9] and local search [8, 10 and 11]

Advantages of DRHS: The harmony memory used in DRHS opposition based learning will have a better search space. The HS is applied to the sub groups of the HM independently and it is regrouped at regular interval to avoid stagnation and premature convergence. Also an opposition harmony is created for each group and among the original and the opposition harmony, the best is chosen for updating the HM. Local search is also performed on the overall best harmonies.

Dynamic Regional Harmony Search with Opposition and Local Learning (DRHS-OLL): The HS variants proposed by various authors improve the optimization performance in terms of best solution, runtime and convergence [12, 13, 14]. Perhaps few hybrids optimization algorithms use HS along with other metaheuristic algorithms like differential evolution (DE) and particle swarm optimization (PSO) [15, 16]. The DRHS-OLL algorithm originally proposed by A.K.Qin and Florence Forbes is used for optimization as it fixes the deficiencies in other proposed algorithms.

Improved strategies in DRHS-OLL [16]:

- Only half of the HM is used to create the solution space and another half is used for opposition-based learning [9].
- The HM is regrouped in each iteration to avoid premature convergence.
- DRHS also generates an opposite harmony by applying HS-OL.
- Group memory is updated with one of the two harmonies
- It reduces premature convergence and stagnation
- Also the local searches done by DRHS-OLL periodically enable robust optimization.

Table 1: Functional Block of Filter Structure

Functions		
255-X	(X∩Y)	Min(X, Y)
(X+Y)/2	(X+Y+1)/2	Max(X, Y)
~ X	(X+Y)/2 + 1	~ (X Y)
~ (X Y)	X/2	X

Image Filter Design Problem: The image filter optimization problem is divided into two parts with estimation as the initial stage followed by filter structure. The harmony memory is initialized with random image filter structure whose functions are defined in table 1. The random structures are improvised based on the quality of the denoised image pixels by calculating the MSE and PSNR. The new filter structure is added to the harmony memory (HM) if it has better performance. This process is done iteratively till the convergence is reached or for a predefined number of iterations.

Thus the functions used to evolve and to optimize the image filter are found by experimenting the operators for image enhancement.

Image Quality Assessment: The quality of reconstructed image can be evaluated using quality metrics (PSNR) and distortion metrics (MSE).

Quality Metrics: Peak Signal to Noise Ratio (PSNR): SNR in decibels (dB) between the original (X) and reconstructed ($\hat{X}$) image of size MXN is defined as:

$$PSNR = 20\log_{10}\left(\frac{2^B - 1}{\sqrt{MSE}}\right)$$

Where, B represents bits per pixel (bpp).

Distortion Metrics: Mean Square Error (MSE): MSE between the original (X) and reconstructed ($\hat{X}$) image is defined as:

$$MSE = \frac{\left\|X - \hat{X}\right\|^2}{MN}$$

An MSE=0 in a reconstructed image indicates that $\hat{X}$ is a perfect reconstruction of X. Increasing values of MSE correspond to increasing error.

RESULTS AND DISCUSSION

The adapted HS algorithm converge various standard test functions and hence proving its convergence property.

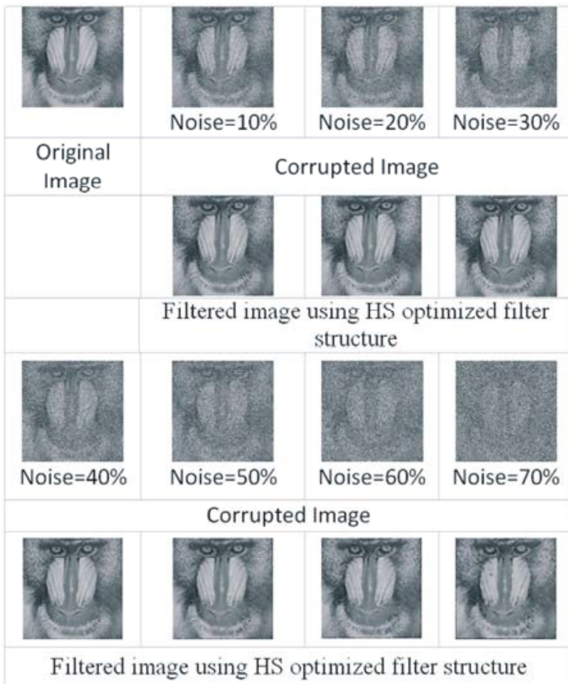

Fig. 2: Denoised images for various noise levels

Table 2: Average MSE and PSNR for the filtered image using the evolved filter

	Proposed filter	
Noise density	MSE	PSNR
10%	1.79	44.96
20%	5.83	41.05
30%	11.54	38.40
40%	19.91	34.97
50%	32.61	33.72
60%	48.78	31.71
70%	96.81	28.78

Table 3: Comparison of PSNR of standard noise removal algorithms for various noise densities (10% to 70%)

	Noise density						
Algorithm	10%	20%	30%	40%	50%	60%	70%
BDND[20]	43.28	38.64	36.37	33.87	32.32	30.72	29.04
ABDND[18]	43.04	38.84	35.60	33.84	32.00	30.90	29.28
LOFBDND[19]	42.50	39.01	36.55	34.33	31.94	28.37	23.28
NASMF[17]	43.12	36.03	36.10	32.16	31.01	29.37	27.64
Proposed Method	44.96	41.05	38.40	34.97	33.72	31.71	28.78

The Evolutionary image filter scheme presented in this paper for the removal of impulse noise which is more efficient in terms of MSE and PSNR. The optimum results achieved within 30th generation with generation run of 50 each to generate better Harmonies. The test image to the evolved filter circuit and its filtered version is shown in figure 2. This shows that the evolved filter structure using HS can efficiently perform the impulse noise removal for impulse noise corrupted images.

The test image is corrupted by impulse noise of various densities ranging from 10% to 70% and the HS algorithm is used to evolve the filter structures. Using the optimized filter structures, the corrupted images are denoised and the calculated MSE and PSNR are shown in table 2.

CONCLUSION

In this paper, the authors have taken an initial step to use the HS for removing impulse noise from the corrupted image. The HS based optimization of image filters has proven performance benefits even for highly corrupted images. HS is effective in removing impulse noise which can be further improved by introducing various other statistics by involving the estimation problem along with denoising filter. The PSNR and MSE metrics also shows significant improvement which are compared with other algorithms available in the literature.

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