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# Decision Based Median Filter using Particle Swarm Optimization for Impulsive Noise

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***Abstract***: *Infrared image sensors and communication medium often introduce impulse noise in image acquisition and transmission. Most commonly available filters to remove impulsive noises are median filters with different versions, but the most important drawbacks identified with them are low noise suppression and edge blurring. To preserve the sharp and valuable information present in the image, the filtering algorithms should preserve the information available in them. The proposed work consists of particle swarm optimization based weight adaptation approach in the design of the filter. The filter weights are adapted and optimized directly to restore a corrupted pixel in a mean square sense. This proposed work results in replacement of noisy pixels by near originals along with its edge direction. The objective parameters used are Peak Signal to Noise Ratio, Mean Absolute Error, and Correlation. This proposed research work is designed at presenting a new filtering framework for impulse noise removal using Particle Swarm Optimization.*

***Keywords:*** *Infrared images, Particle Swarm Optimization, De-noising, Non-linear filters, Decision Based Median Filter.*

## I. Introduction

Infrared images often suffer from impulse noise due to the errors generated in sensory devices or communication channels. The most extensively recognized non-linear filter is the median filter which is an effective technique to remove impulsive noise from images. To remove impulse noise, various non-linear filters have been developed in the literature [1, 3-7]. Various non-linear filters available are Simple Median (SM), Weighted Median (WM), Adaptive Median (AM) and Decision Based Adaptive Median (DBAM) filters with respect of corrupted images with medium noise density. Even though a median filter and its variants usually perform impulse noise removal effectively, but they destroy the image signal structure (edges) and hence the image gets blurred. In this scenario there is a need for adapting the filter weights to the direction of edges accordingly. In order to over come the drawbacks of the existing methods a new method is proposed, which preserve the edges and fine details of the original image and overcomes the drawbacks of the existing methods.

Optimization tools like Genetic Algorithm (GA), Particle Swarm Optimization (PSO) can play a role in optimizing the filter weights in preserving the edges. In noise filtering approaches that incorporate GA to optimize L-filter using an artificially generated test training image, the original image has been used as target while optimizing the filter. A part of the original image is used to train the prominent parameters like tap weights of the filter. But having the original image itself at the receiver section in any communication system is not always feasible. Thus the independence of the noise filter with respect to the original image can make the filtering process, self evolutionary [4]. The proposed self evolutionary filter uses PSO further to adapt weights of the filter. This study commences with an introduction about the filtering techniques. The Selective Filtering Framework has been explained following a brief about the Impulse Noise model. It concludes with a detailed explanation about the proposed filtering algorithm justified by the Results and Discussion.

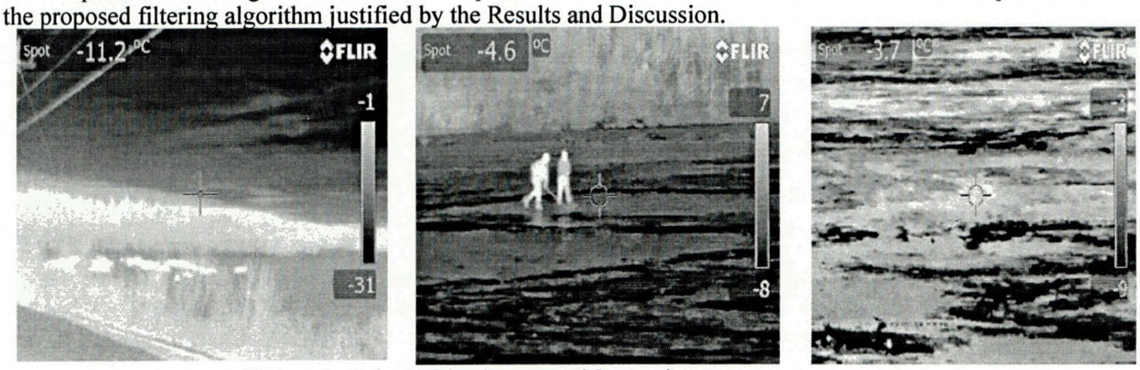


**Figure 1: Infrared ice images with varying temperature range.**

The method used in this paper has been organized in the following manner, section 2 describes explanation of the proposed method, section 3 describes the results and discussions, section 4 gives conclusion and finally all the references been made for completion of this work.

## II. Explanation of the Proposed Method

A particle swarm optimizer (PSO) is a population-based stochastic optimization algorithm modeled after the simulation of the social behavior of bird flocks. Another major difference is that, in PSO, each individual benefits from its neighbors and history. PSO is easy to implement and has been successfully applied to solve a wide range of optimization problems such as continuous nonlinear and discrete optimization problems [1, 2, 9].

**Impulse noise image model:** Let $I_n(x, y)$ with $1<x<X$ and $1<y<Y$ be the expected noise affected image of size (X, Y) established at the receiver. The noisy image can be shown as:

$$I_n(x,y)=\begin{cases} I(x,y)\ with\ probability\ 1-P_1-P_2 \\ I_s\ with\ probability\ P_1 \\ I_p\ with\ probability\ P_2 \end{cases}$$

Where:
$I(x, y)$ = The original transmitted image
$I_S$, $I_P$ = The constant amplitudes corresponding to the maximum (salt) and minimum (pepper) intensity of the peak noise
$P_1$, $P_2$ = The probabilities of occurrence of pixel being corrupted by maximum and Minimum impulsive noise respectively

In the presence of impulse noise model, only certain samples of the original signal are corrupted and others remain unaffected. The noise $\eta$ is characterized by the magnitude of the impulses and their probability of occurrence 'p'. Since 'p'<< 1 mostly, it is useful to filter an input sample, to reduce blurring of the signal. Therefore, the filtering process consists of two parts which is shown in Fig 2:

Ascertaining whether the input sample considered (center pixel in the processing window) is corrupted by an impulse
In such case replacing the corrupted samples by a value estimated from its neighbors. Otherwise passing the samples to the output unprocessed.

**Impulse noise and Edge detection:** Adaptive median filter based impulse noise detector is used in this approach which detects impulses accurately. An image window W around a pixel $X_{p,q}$ is defined as:

$$W_{p,q}(X)=\{X_{i,j}\mid p-m\leq i\leq p+m,\ q-m\leq j\leq q+m\}$$

Where, 'm' = A positive integer that determines the window size
(p, q) = The index of the current pixel

The corrupted pixels belong to a set $\{W_{min}, W_{max}\}$, where $W_{min}$ is the minimal pixel value and $W_{max}$ is the maximum pixel value. Decision Based Adaptive median filtering of the corrupted image $X_{i,j}$ yields a filtered image M and a corrupted pixel signifying the presence of noise is assigned a flag matrix 'f ' given by:

$$f(i,j)=\begin{cases} 1\ if\{(X_{i,j}\neq M_{i,j})\ \&\ X_{i,j}\in\{W_{min},W_{max}\}\} \\ 0\qquad else \end{cases}$$

The edges in the image are obtained by using prewitt filter mask which is shown in Fig 2. When the noisy pixels are on edges, the non noisy pixels along that edge are considered in filtering process.

| | | |
|---|---|---|
| 1 | 1 | 1 |
| 0 | 0 | 0 |
| -1 | -1 | -1 |

**Figure 2: Prewitt filter mask**

**Proposed method:** The proposed filter uses self evolutionary processing, which uses only selective pixels of the corrupted image as the reference and operates only over the noisy pixel locations. The filter weights are optimized in such a way that they are qualified as the robust weights with the fitness function evaluation. Figure 3 shows the flow of the Decision Based Adaptive Median filter using Particle Swarm Optimization (PSO).

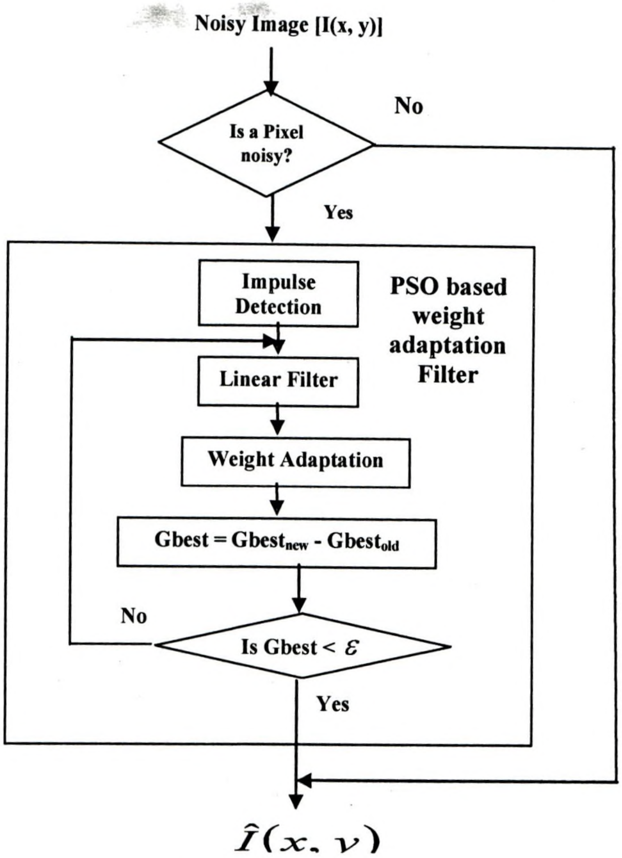


**Figure 3: Decision Based Median Filter using Particle Swarm Optimization (PSO)**

**PSO based weight adaptation filter:** An adaptive window structure in which each noisy pixel is replaced by its neighborhood pixels weighted with the random weights are provided by PSO. The following steps give the flow of the filtering scheme:

A local vector L = { $l_1$, $l_2$,...,$l_N$} is formed with noisy pixels at locations given by the flag matrix f. For each element in the local vector L, form a search region $S_m$ whose size m x m is adaptive, as there are insufficient good pixels around a noisy pixel. This situation arises when the noise density goes higher. The size of the search region m x m varies as:

$$m = \begin{cases} 5 & \tau_1 \leq N_1 \\ 7 & \tau_2 \leq N_2 \end{cases}$$

where, $\tau_1$ and $\tau_2$ are the predefined threshold values that define the number of non-noisy pixels for each window (say if more than 50% of total number of pixels in the operating window is corrupted then the search region has to be switched to the next possible window). $N_1$ is the number of non-noisy pixels in $5X5$ window.
A candidate vector $C_N$= {$c_1$, $c_2$, ... ,$c_N$} whose elements are the pixel locations from the search region $S_m$ but not the member of L, is defined as:

$$C_N = \{c_1, c_2, \ldots, c_N \mid c_i \in S_m \text{ and } c_i \notin L\}$$

Let $P_N$= {$p_1$, $p_2$, ..., $p_N$ } be the vector of non noisy pixels corresponding to the elements in the vector $C_N$. The vector $P_N$ has been reformulated to $P_{MN}$ = {$P_{1N}$, $P_{2N}$, $P_{3N}$} where $P_{1N}$ is the number of non noisy pixels in 3x3 window, $P_{2N}$ is the number of non noisy pixels in 5x5 window excluding $P_{1N}$ and $P_{3N}$ is the number of non noisy pixels in 7x7 window excluding $P_{1N}$ and $P_{2N}$ Let $A_{1N}$, $A_{2N}$ and $A_{3N}$ are the weight vectors generated by PSO during the course of algorithm corresponding to $P_{1N}$, $P_{2N}$ and $P_{3N}$ respectively such that $\sum A_{1N} = X_1$, $\sum A_{2N} = X_2, \sum A_{3N} = X_3$ *and* $\sum X = 1$. The image is restored by applying the weights $A_{MN}$.

**Directional optimization of filter weights:** The estimating strategy is devised as to minimize the Mean Square Error between the filtered pixel and the neighboring non noisy pixels. Error minimization is achieved by finding the major four directions in which the filtered pixel actually orients with a minimal error. Figure 4 shows a $5X5$ window with 'S' as the center and filtered pixel, along with other remaining pixels in four different directions given by D1, D2, D3 and D4. With the fixed $5X5$ window being taken around the filtered pixel, the deviation of the filtered pixel $\hat{I}$ from other non-noisy pixels in the directions D1 (90°), D2 (0°), D3 (45°) and D4 (135°) is found individually using:

$$DMSE_k = \frac{1}{n}\sum_{i=1}^{n}\left(\hat{I} - D_{ki}\right)^2$$

where, $D_{ki}$ denote the $i^{th}$ non noisy pixel present in the direction k and 'n' denotes the number of non noisy pixels in the direction k.

| | | | | |
|---|---|---|---|---|
| D4 | | D1 | | D3 |
| | D4 | D1 | D3 | |
| D2 | D2 | S | D2 | D2 |
| | D3 | D1 | D4 | |
| D3 | | D1 | | D4 |

**Figure 4: A 5X5 window showing filtered pixel 'S' with its directional neighbors D1, D2, D3 and D4**

The proposed filter is recursive in nature which means that, the filtered pixel will be able to take part in the course of filtering the noisy pixel. Once the $i^{th}$ noisy candidate has been filtered, correspondingly the flag matrix gets updated such that the respective location in the local vector L is detached and it can be achieved by:

$$L_{i+1} = \{l_k \in L_i\},\ k = 1,2,\ldots,N \ and \ k \neq i$$

$l_k$ is the location of the noisy pixel, filtered in the earlier iterations.

**Optimization of filter weights:** Particle Swarm Optimization begins with an initial set of random solution. Each potential solution in the set called particle is given a random velocity and is propagated through the problem space. The particles have memory and share information of their previous best position and the over all best position ever traveled by a particle in the swarm. The algorithm of the PSO weight adaptation is given below [4].

**Algorithm:** How to optimize filter weights using Particle Swarm Optimization:

Step 1:□Initialize the weights $x_i$ and the rate $v_i$ for all I(x, y)

Step 2: Let n be the size (population) of solution space. Let the fitness function f be the mean square error defined as:

$$MSE_j = \frac{1}{n}\sum_{i=1}^{n}\left(\hat{I} - d_{ji}\right)^2$$

For every member $1 \leq i \leq n$ of the solution space

Step 3: Generate learning factors w, c1, c2 and the random values b1, b2

Step 4: Update the rate as:

$$V_i = \omega v_{iold} + c_1 * b_1 * (p_{id} - x_{iold}) + c_2 * b_2 * (p_{gd} - x_{iold})$$

Update the weights as:

$$x_i = x_{iold} + v_i$$

Step 5: When $f(x_i) < f(P_{id})$, update the Individual Best ($P_{id}$) for i (particle)

Step 6: When $f(P_{gd}) < f(x_i)$, update the Global Best ($P_{gd}$)

The above algorithm is iterated until:

$$P_{gdnew} - P_{gdold} \leq \varepsilon$$

This convergence yields $P_{gd}$, the optimal set of weights

## III. Results and Discussions

The results are generated by using matlab simulations. The methodology is examined with infrared images with the temperature ranging from -24$^0$C to 9$^0$C. Infrared images are first converted to gray scale images and then these images are filtered by standard non linear filters such as median filter, weighted median filter, adaptive median filter, decision based median filter and proposed method. Initially Infrared images have been corrupted by impulse noise with noise density levels ranging from 10-90%. Median filter, weighted median filter, adaptive median filter, decision based median filter and proposed method are compared using the performance metrics such as Peak Signal to Noise Ratio (PSNR), Mean Square Error (MSE), Mean Absolute Error (MAE) and Correlation.

$$PSNR(I,\hat{I}) = 10\log_{10}\left(255^2 / MSE(I,\hat{I})\right)$$

where $$MSE(I,\hat{I}) = \frac{1}{MXN}\sum_{i=1}^{M}\sum_{j=1}^{N}\left(I_{ij} - \hat{I}_{ij}\right)^2$$

M and N = The size of the image

$I(x, y)$ = The original image for evaluating the quality of the various filters

$\hat{I}(x, y)$ = The image obtained after applying the respective filters

$$MAE(I,\hat{I}) = \frac{1}{MXN}\sum_{i=1}^{M}\sum_{j=1}^{N}\left|I_{ij} - \hat{I}_{ij}\right|$$

Figure 5 shows the results of various filters and proposed filter, Fig 5b shows 50% noise intensity induced to the original Infrared image. Various filter algorithms are applied on the noisy Infrared image and the corresponding results are shown in Fig. 5( c)-(f). Proposed PSO based filter result is shown in Fig. 5(g). Most of the non-linear filters fail to preserve the sharp details in the image while the proposed method preserves the edges carefully in the way that it minimizes the error.

Table.1 provides the results of simple median filter, weighted median filter, adaptive median filter, decision based adaptive median filter and proposed PSO filter. The performances of all these filters are tested by using the performance metrics such as PSNR, MSE, MAE [4] and Correlation. From the Table1 it is found that proposed PSO filter produces the highest results for the above mentioned metrics.

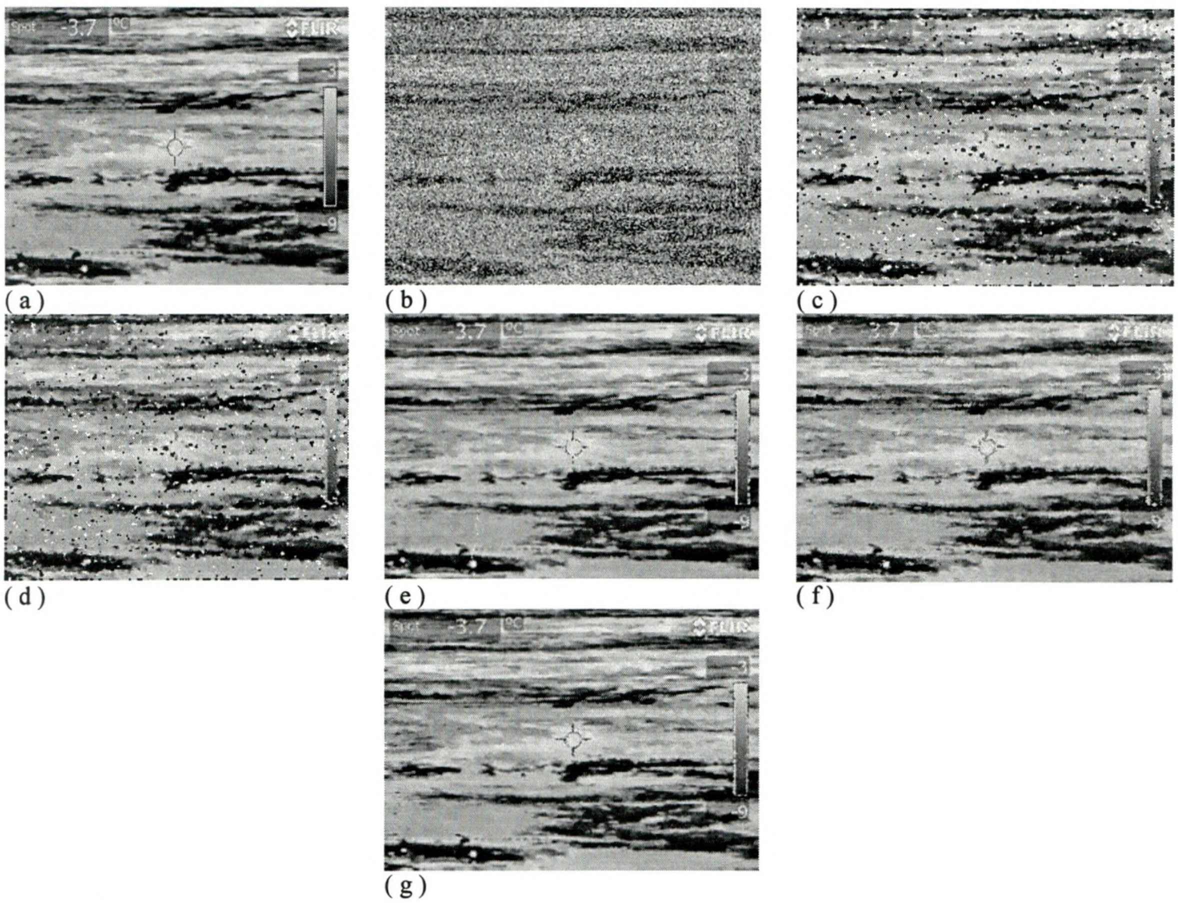

**Figure 5: ( a) Original Image ( b ) Noisy image with Salt & Pepper noise density 40%, ( c ) Simple Median Filter (17.70dB), (d) Weighted Median Filter (17.89dB), (e) Adaptive Median Filter (20.52dB), ( f ) Decision Based Adaptive Median Filter (26.62dB), ( g ) *Proposed Method (29.04dB)***

**Table.1: The performance metrics results for Simple median filter, weighted median filter, adaptive median filter, decision based adaptive median filter and proposed PSO filter.**

| Noise in (%) | Simple Median Filter | | | Weighted Median Filter | | | Adaptive Median Filter | | | Decision Based Median Filter | | | Proposed Method | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | PSNR | MAE | Corrln | PSNR | MAE | Corrln | PSNR | MAE | Corrln | PSNR | MAE | Corrln | PSNR | MAE | Corrln |
| 10 | 27.82 | 4.67 | 0.98 | 28.29 | 4.70 | 0.99 | 21.13 | 3.75 | 0.93 | 35.15 | 0.87 | 1.00 | **38.08** | **0.45** | **1.00** |
| 20 | 24.62 | 6.34 | 0.97 | 25.07 | 6.30 | 0.97 | 20.96 | 4.30 | 0.93 | 31.15 | 1.88 | 0.99 | **33.62** | **1.07** | **1.00** |
| 30 | 21.13 | 9.01 | 0.92 | 21.30 | 8.95 | 0.93 | 20.78 | 5.02 | 0.93 | 28.67 | 3.12 | 0.99 | **31.15** | **1.82** | **0.99** |
| 40 | 17.70 | 13.53 | 0.85 | 17.89 | 13.59 | 0.85 | 20.52 | 5.88 | 0.92 | 26.62 | 4.55 | 0.98 | **29.04** | **2.72** | **0.99** |
| 50 | 14.41 | 21.95 | 0.71 | 14.39 | 22.02 | 0.71 | 20.22 | 6.94 | 0.91 | 25.02 | 6.07 | 0.97 | **27.61** | **3.68** | **0.98** |
| 60 | 11.93 | 33.69 | 0.57 | 11.90 | 33.82 | 0.56 | 19.70 | 8.42 | 0.90 | 23.46 | 7.86 | 0.96 | **26.02** | **4.86** | **0.98** |
| 70 | 9.77 | 50.14 | 0.41 | 9.75 | 50.36 | 0.40 | 18.18 | 11.40 | 0.87 | 22.07 | 9.87 | 0.94 | **24.71** | **6.17** | **0.97** |
| 80 | 7.83 | 73.70 | 0.24 | 7.81 | 73.88 | 0.24 | 14.81 | 19.72 | 0.74 | 20.63 | 12.50 | 0.91 | **23.20** | **8.05** | **0.95** |
| 90 | 6.34 | 99.95 | 0.11 | 6.33 | 100.10 | 0.11 | 9.97 | 47.64 | 0.43 | 17.91 | 18.28 | 0.84 | **20.24** | **12.29** | **0.91** |

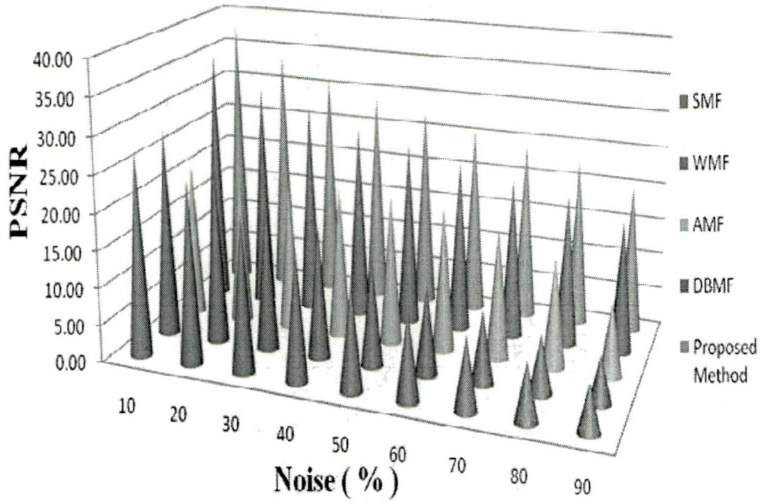


**Figure 6: Peak Signal to Noise Ratio for various noise levels with various Median filters and proposed method**

## IV. Conclusion

Infrared images contains the impulse noise, hence to remove impulse noise from infrared images, Non linear filters such as median filter, weighted median filter, adaptive median filter and decision based adaptive median filter are used and compared with the proposed filter. Particle Swarm Optimization (PSO) filter is the proposed image filter, which is used for denoising the corrupted pixels by impulsive noises in gray-level images. In proposed filter, the weights are optimized by using PSO which minimize the mean square error rate. Experimental results demonstrate that the proposed filter can effectively de-noise the gray-level images corrupted by impulse noises when compared with other methods used in this paper. It is found that the proposed filter provides higher PSNR and correlation, and lower MSE and MAE values when compared with the existing versions of filters.

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# Cell Nuclei segmentation in Pap smear images using Optimized Binarization technique with Adaptive Wiener Filter

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## *Abstract*

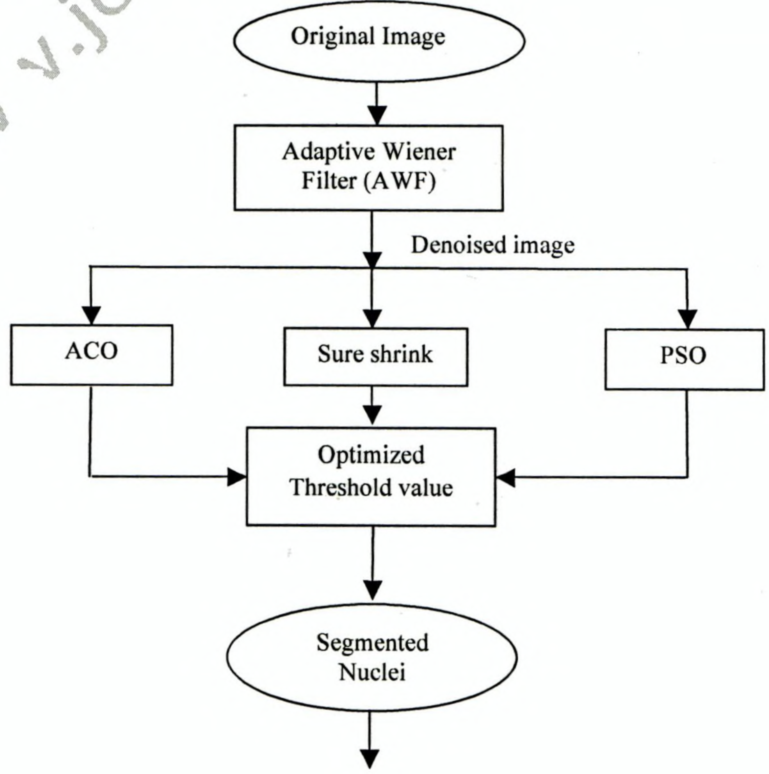
*Cervical cancer is the second leading reason of death among women in India. The most common screening technique is Pap smear test which is used to detect abnormal growth of cervical cells at an early stage. The accuracy rate of cervical cancer diagnosis using Pap smear images depends on the segmentation of the cell nuclei. This paper proposes the optimized binarization technique with Adaptive Wiener Filter (AWF) for the cell nuclei segmentation in two key steps. First, the Adaptive Wiener Filter is used for the noise removal as well as to preserve the details of the Pap smear images. Followed by, the threshold value is being obtained from the sure shrinkage method, Ant Colony Optimization and Particle swarm optimization for the exact segmentation of cell nuclei from Pap smear images. Due to the limitations in the segmentation techniques, the loss of cell nuclei gets a raise which affects the quality and efficiency of cervical cancer detection. To know about the loss in the number of cell nuclei during segmentation step, the number of nuclei is counted from the segmented images and cell count results are compared with each other. From the results, it is found that the Adaptive Wiener Filter in combination with PSO based threshold segmentation performs well in terms of MSE, cell nuclei count, sensitivity and specificity.*

*Keywords- Cervical cancer, Adaptive Wiener Filter (AWF), Optimized threshold segmentation, Ant Colony Optimization, Particle swarm optimization*

## 1. Introduction

In developing countries like India, cervical cancer is the most common gynaecological cancer and one of the most common cancers among women worldwide. It is caused by Human PapillomaVirus (HPV) infection. In 2004, cervical cancer was the third largest cause of cancer mortality in India with incidence rate of 30.7 per 100,000 women [1]. As of now, the incidence and mortality rates have decreased gradually over the past few decades, mainly due to the widespread use of the Pap smear test which detects cervical cancer and precancerous lesions easily and accurately.

Cervical screening using Pap smear images is one of the most successful ways of detecting and diagnosing the cancer even at an early pre-cancerous stage. However, Pap smear test does not always produce good diagnostic performance due to bad samples, technical and human errors [6]. Due to limitations of diagnosis performance by Pap smear test, computer aided visualization and intelligent diagnosis has to be developed to increase the diagnostic performance of the Pap smear test.



Performance Evaluation based on MSE, Cell Count, Sensitivity and Specificity

**Fig.1: Block Diagram of proposed Cell Nuclei segmentation in Pap smear images**

In this work, initially the original Pap smear image is given as input to the filter for the removal of noise from the original image. Next, the optimized threshold value is being obtained from ACO and PSO for the cell nuclei segmentation. Finally, the cell nuclei are segmented from the denoised images and performance evaluation is done.

The paper is structured as follows, the restoration procedure adopted in the work is detailed in the section 2, section 3 discusses the optimization of binarization technique for cell segmentation, section 4 discusses the performance evaluation results for the taken image dataset and section 5 gives the conclusion and followed by references used.

## 2. Suitable Restoration technique for Pap smear images filtering

Microscopic images are often corrupted by Poisson noise [8]. For the proper diagnosis of diseases, the pre-processing step in Pap smear images is vital to remove the noise and to increase the contrast. Removing noise from any processed images is very necessary. However, noise should be removed in such a way that essential information of image should be preserved. As per the result derived in the previous work with the same dataset, the Adaptive Wiener Filter (Wiener Filter) is the best filter to restore the original image which is corrupted by noise.

### 2.1 Adaptive Wiener Filter

The Adaptive Wiener Filter was proposed by Norbert Wiener in 1940 and its purpose is to reduce the amount of noise present in an image. It takes a statistical approach to solve its target. The aim of the process is to have minimum mean- square error. which means, the difference between the original signal and the new signal should be as less as possible.

### Procedure for Adaptive Wiener Filter

**Step 1:** For the given input images, the local mean and variance around each pixel is calculated by using the following equation,

$$\mu = \frac{1}{NM}\sum_{n_1,} \propto (n_1, n_2) \quad \text{………………………………} (1)$$

$$\sigma^2 = \frac{1}{NM}\sum_{n_1, n_2 \in n} a^2 (n_1, n_2) - \mu^2 \quad \text{………………………………} (2)$$

where, $\mu$ is the mean and $\sigma^2$ is the variance and $\measuredangle$ is the *N*-by-*M* local neighborhood of each pixel in the image.

**Step 2:** Local variance from the given image is obtained by applying wiener function in a linear filter.

**Step 3:** If the variance calculated for the given image is large, the wiener performs little smoothing.

**Step 4:** when the variance is small the wiener performs more smoothing.

The first step in the automatic segmentation of cell nuclei is the pre-processing of the Pap smear images. After the input image is read into memory, its size should be resized to 400*400 sizes. The resizing is done to preserve the image aspect ratio. Then an Adaptive Wiener Filter is applied to increase the contrast in bright cell regions and to remove noise from the image.

## 3. Optimization of binarization technique for cell segmentation

The correct characterization of Pap smear slides for the contents of the pap smear depends on the general appearance of the nuclei. This is based on the fact that the nucleus is an important structural part of the cell which exhibits significant changes when a cell is affected by a disease [6]. In pathological situations, the nucleus may exhibit disproportionate enlargement, irregularity in form and outline. The identification and quantification of these changes in the nucleus morphology and density contribute in the discrimination of normal and abnormal cells in Pap smear images. Segmentation of cells in cytological images is a fundamental subject of quantitative analysis. Because the malignant or abnormal characteristics of cancer cells are contained in cell nucleus, so the isolation of cell nucleus is an important task of segmentation.

### 3.1 Proposed Binarization Techniques

The proposed optimized threshold based segmentation method comprises of two subtasks,

(i) optimized threshold technique selection and

(ii) Applying that optimized threshold to the Pap smear images.

The selection of threshold is the most important step. In various application of medical image processing, the gray levels pixel intensity of nuclei is entirely different from the gray level intensity of the cytoplasm and backgrounds. So, the thresholding method will become a straightforward but successful tool to separate objects from the background. The performance measured and outcome of the optimized threshold based segmentation are shown in Fig.2, Fig.3, Fig.4 and Fig. 5.

### 3.1.1Particle swarm optimization (PSO)

PSO is the population based stochastic optimization technique. Firstly, based on the given input image, the particles position and velocity is initialized and the iteration count i is set as 1. Secondly, based on the particles position and velocity, the fitness value is calculated and result is stored. Next, the iteration count is incremented and also the particles position and velocity is updated. Based on the updated values, the fitness value is calculated and compared with the stored value. Finally, the threshold value is displayed when the iteration reaches the maximum. "In recent years this method has gained recognition over its competitors due to its simplicity, superior convergence characteristics and high solution quality" [7].

**PSO Procedure**

**Step1:** Initialize N particles with random positions $x_1$ , $x_2 \ldots x_N$ and velocities $V_i$ where i=1,2,..N.

$$V_{ij}^{k+1} = wV_{i,j}^{k} + c_1 r_1 (pbest_{ij}^{k} - x_{ij}^{k}) + c_2 r_2 (gbest_{j}^{k} - x_{ij}^{k}) \quad \ldots\ldots\ldots\ldots\ldots. (3)$$

where, X and V represent the particle's position and its corresponding velocity in search space respectively with K iteration.

**Step2:** Velocity and position of each particle in next iterations is calculated using the Eq. (4).

$$x_{ij}^{k+1} = x_g^k + v_g^k \qquad \ldots\ \ldots\ldots\ \ldots\ (4)$$

**Step3:** Update global best positions.

If *f (pbesti)* < *f (xi)*, then *pbesti* = *xi*, and search for the maximum value *fmax* among *f (pbesti)*, If max *f (gbest)* < *fmax, ,then gbest = x max, xmax* is the particle associated with *fmax.*

**Step4:** Update velocity: update the *i*th particle velocity using the Eq. (4) restricted by maximum and minimum threshold *vmax* and *vmin* .

**Step5:** Repeat step 2 to 5, until the optimal solution is obtained.



### 3.1.2 Ant Colony Optimization (ACO)

Ant Colony Optimization (ACO) is a pattern for designing metaheuristic algorithms for combinatorial optimization problems. Initially, the first ant is selected from the given input images. The path for each ant is selected on the basis of the amount of "pheromone trail" present on the possible paths starting from the current node of the ant. In case of equal or no pheromone on adjacent paths, ants randomly choose the path. Ant then reaches the next node and again does the path selection process. This process continues till the ant reaches the starting node. This finished tour gives the best threshold.

**Ant colony optimization procedure**

**Step 1:** Choose the first ant k=1

**Step 2**: Evaluate ant value.

If k(ant)<aver(ant), generate new ant k again.

Else transit to ant j (1<=j<= K) according to the transition rule

**Step 3**: In the neighbourhood of ant j with a radius of r, randomly search the better ant to update ant j. Copy the ant j to the best ant g if j(ant>g(ant). Update ant k with ant j

**Step 4:** Continue to choose the next ant k=k+1

**Step 5:** Update Pheromone and neighbour radius=0.9

**Step 6:** Return the best ant g.

### 3.1.3 Sure Shrink Algorithm

Sure shrink is a threshold selection method, in which a separate threshold is computed for each sub band. Next, it computes the value that minimizes Stein's Unbiased Risk Estimator, size of the image and noise variances to calculate the sure shrink threshold by using the soft thresholding rule.

**Procedure**

**Step 1:** The sure shrink threshold is calculated by using the formula

$$t^* = \min\left(t, \sigma\sqrt{2logn}\right) \quad \ldots\ldots\ldots\ldots (5)$$

where, t is the value that minimize Stein's Unbiased Risk Estimator , $\sigma$ is the noise variance, n is the size of the images and $t^*$ is the sure shrink threshold.

**Step 2**: Minimize the mean squared error by minimizing the function

$$f(\lambda) = N + ||g(x)||2 + \frac{2\Sigma d}{dxk(gk(x))} \quad \ldots\ldots\ldots\ldots (6)$$

where (x) is the threshold function minus the value for each value of , k = 1, 2, …N

**Step 3**: Once the size of the given image, noise variance and minimize Stein's Unbiased Risk Estimator is found. The sure shrink threshold is calculates and given as output.

## 4. Performance Evaluation

In this section, the result of the segmented nuclei which is obtained from the optimized threshold based segmentation is evaluated based on the subjective and objective evaluations. The subjective evaluation of segmented nuclei obtained using the proposed method is shown in Fig.2. Fig.3 shows the objective evaluation based on MSE, in view of the fact that their MSE is lower for AWF in combination with PSO based optimized threshold segmentation method. From the cell nuclei result, it is inferred that cell nuclei loss during segmentation is low for AWF in combination with PSO based optimized threshold segmentation method which is shown in fig.4. Even though the cell nuclei loss is high for AWF in combination with sure shrink based optimized threshold segmentation, the sensitivity and specificity remains high. So, AWF in combination with PSO based optimized threshold segmentation method is the best method for cell nuclei segmentation in Pap smear images due to the minimized cell nuclei loss.

### 4.1 MSE (Mean Square Error)

Mean Square Error (MSE) is one way of measuring the similarity to compute an error signal by subtracting the test signal from the reference, and then to compute the average energy of the error signal. The mean-squared-error (MSE) is the simplest, and the most widely used for image quality measurement.

$$\text{MSE}=\frac{1}{MN}\sum_{i=1} M \sum_{j=1} N(x(i,j) - y(i.j))^2 \quad \ldots\ldots\ldots\ldots (7)$$

Where x (i, j) represent the original image and y(i , j) represent the denoised (modified) image and i and j are the pixel position of the M×N image.MSE is zero when x(i, j) = y(i, j) .

### 4.2 Cell Nuclei count

To count the cell nuclei from all the segmented images, the cell nuclei's are counted manually from each of the resultant images and original images to yield a total cell nuclei count within an image. Then, the number of nuclei detected by the proposed segmentation technique is compared with the original images cell count. From the cell nuclei count results, it is inferred that the optimized threshold based AWF in combination with PSO shows good result when compared with other methods due to the minimum number of cell nuclei count loss during segmentation step.

### 4.3 Sensitivity and specificity

The fundamental measures to quantify the cell count accuracy of a test include sensitivity and specificity. The sensitivity of a nuclei segmentation test quantifies its ability to correctly identify nuclei as nuclei. It is the proportion of true positives that are correctly identified by the test, given by:

$$Sensitivity = \frac{True\ Positives}{True\ Positives + False\ Negatives} \quad \ldots\ldots\ldots (8)$$

The specificity is the ability of a test to correctly identify whether the artifacts are identified as nuclei. It is the proportion of true negatives that are correctly identified by the test, given by:

$$Specificity = \frac{True\ Negatives}{True\ Negatives + False\ Positives} \quad \ldots\ldots\ldots. (9)$$

| Original Images | Nuclei segmentation (AWF+Sure shrink based threshold) | Nuclei segmentation (AWF+ACO based threshold) | Nuclei segmentation (AWF+ PSO based threshold) |
|---|---|---|---|

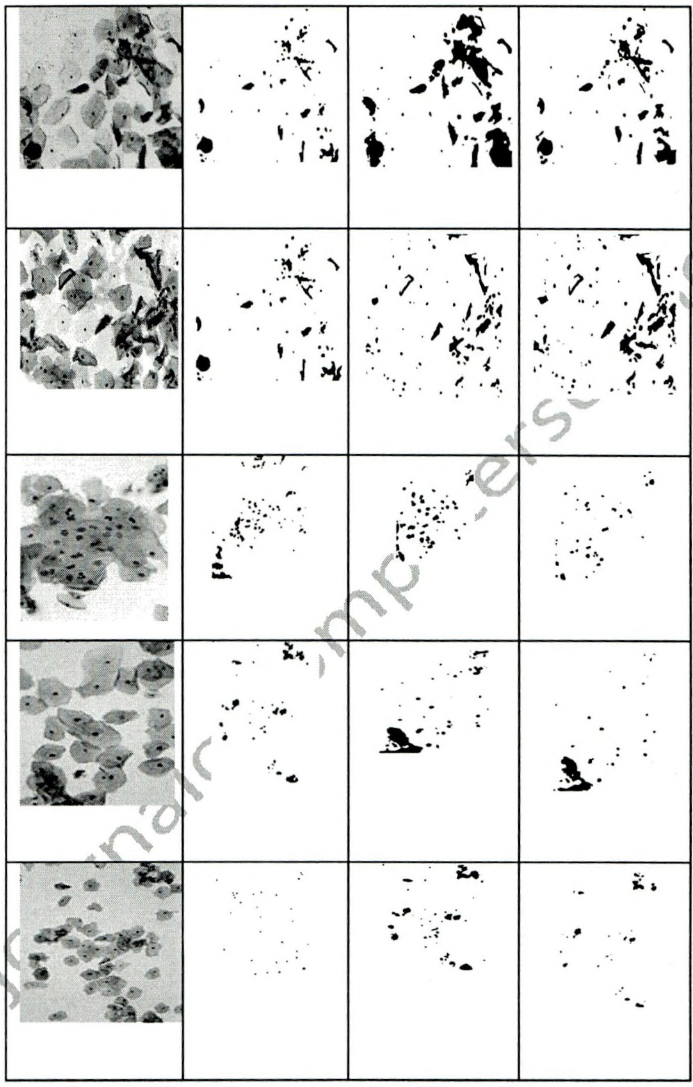


**Fig.2: Subjective comparison results of original and segmented nuclei images using proposed techniques**

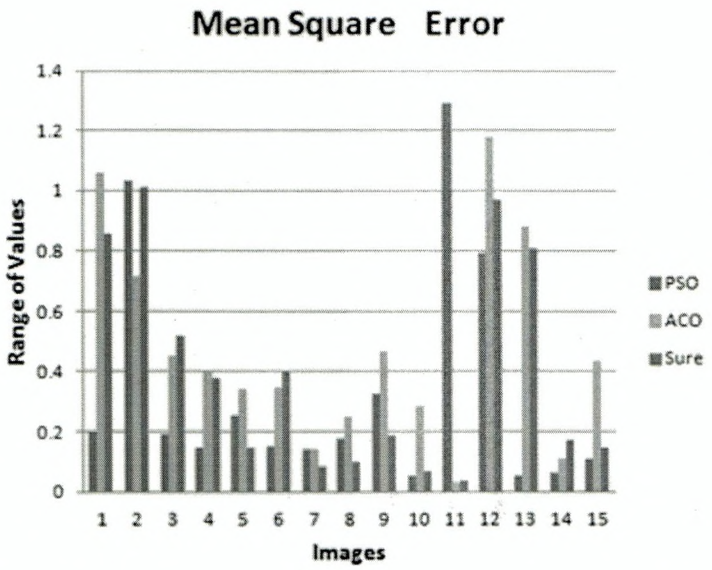
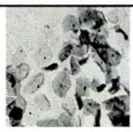
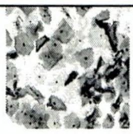
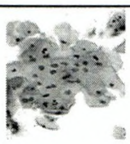



**Fig 3: MSE metric comparison results for Adaptive Wiener Filter in combination with sure shrinkage method, ACO and PSO based threshold segmentation.**



| S.No | Images | Original Images [Nuclei count] | AWF+ Sure shrink based threshold [Nuclei count] | AWF+ ACO based threshold [Nuclei count] | AWF+ PSO based threshold [Nuclei count] |
|---|---|---|---|---|---|
| 1 |  | 41 | 31 | 33 | **39** |
| 2 |  | 53 | **49** | 33 | 43 |
| 3 |  | 47 | 6 | **34** | 27 |

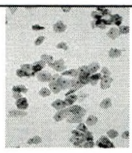
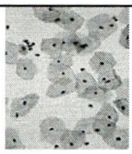
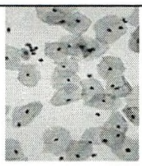
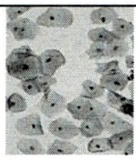
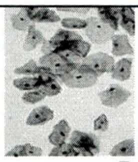
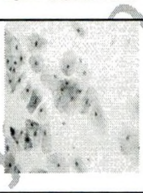
| | | | | | |
|---|---|---|---|---|---|
| 4 |  | 46 | 4 | 32 | **38** |
| 5 |  | 43 | 11 | 28 | **34** |
| 6 |  | 44 | 2 | **37** | 36 |
| 7 |  | 35 | 21 | 32 | **34** |
| 8 |  | 41 | 16 | 32 | **36** |
| 9 |  | 40 | 11 | 25 | **32** |
| 10 |  | 138 | 76 | 119 | **124** |

**Fig.4: Comparison results of Adaptive Wiener Filter in combination with sure shrinkage, ACO and PSO based threshold segmentation in terms of cell count.**

| Performance Metrics | AWF+ Sure shrink based threshold [Nuclei count] | AWF+ ACO based threshold [Nuclei count] | AWF+ PSO based threshold [Nuclei count] |
|---|---|---|---|
| **Sensitivity** | 0.462 | 0.217 | 0.248 |
| **Specificity** | 0.921 | 0.813 | 0.868 |

**Fig.5: Sensitivity and Specificity values for Adaptive Wiener Filter in combination with sure shrink, ACO and PSO based threshold segmentation**

## 5. Conclusion

This paper presented a comparison of optimized threshold based segmentation method by measuring their performance with evaluation metrics. In this paper, the Adaptive Wiener filter is used to restore the image from noise and for strengthening the segmentation method; an optimized threshold based segmentation method is used in combination with AWF for the exact cell nuclei segmentation. With this, the number of nuclei is counted manually from the segmented images to identify the cell nuclei loss during the segmentation step. From the MSE result, it is inferred that the AWF in combination with PSO based optimized threshold segmentation has smaller value. According to the cell nuclei count, the loss of cell nuclei during segmentation step is comparatively lesser than others with the specificity value of 0.217.

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