

# Mutation based Bacterial Foraging Technique cascaded with Wiener Filter To Remove The Speckle Noise of Face Images

Kanchan Lata Kashyap  
 M. tech(P)  
 DIMAT Raipur

Sanjivani Shantaiya  
 Reader (CSE Deptt.)  
 DIMAT Raipur

## ABSTRACT

This paper presents a new approach for the removal of noise from the face images. The approach involves removal of noise from the image by cascading the Mutation based bacteria foraging technique with Wiener filter. In reality the noises that may embed into an image document will affect the performance of face recognition algorithms. Noises are of two type additive and multiplicative noise. Speckle noise is multiplicative noise, so it's difficult to remove the multiplicative noise as compared to additive noise. Face images will be tested from database in noisy environment of speckle noise. The proposed method uses Wiener Filter and Mutation based bacteria Foraging technique (MBFO) has to be used for the removal of speckle noise.

## General Terms

Data reduction, pre-processing, face recognition

## Keywords

Wiener Filter, median filter, speckle noise.

## 1. INTRODUCTION

An image is often corrupted by noise since its acquisition or transmission. The goal of de-noising is to remove the noise while retaining as much as possible the important signal features of an image. A vast literature has emerged recently on signal de-noising using nonlinear techniques, in the setting of additive white Gaussian noise. The image analysis process can be broken into three primary stages which are pre-processing, data reduction, and features analysis. Removal of noise from an image is the one of the important tasks in image processing. Depending on nature of the noise, such as additive or multiplicative noise, there are several approaches for removal of noise from an image [1]-[2].

## 2. MATHEMATICAL FORMULATION OF NOISE

Mathematically the image noise can be represented with the help of the equations given below:

$$V(x, y) = g[u(x, y)] + \eta(x, y) \dots \dots \dots (1)$$

$$g[u(x, y)] = \int \int h(x, y; x', y') u(x', y') dx' dy' \dots (2)$$

$$\eta(x, y) = f[g(u(x, y))] \eta_1(x, y) + \eta_2(x, y) \dots (3)$$

Here  $u(x, y)$  represents the objects (means the original image) and  $v(x, y)$  is the observed image. Here  $h(x, y; x', y')$  represents the impulse response of the image acquiring process. The term  $\eta(x, y)$  represents the additive noise which has an image dependent random components  $f[g(w)] \eta_1$  and an image independent random component  $\eta_2$ . A different type

of noise in the coherent imaging of objects is called speckle noise. Mathematically Speckle noise can be formulated as

$$V(x, y) = u(x, y)s(x, y) + \eta(x, y) \dots \dots (4)$$

Where the speckle noise intensity is given by  $s(x, y)$  and  $\eta(x, y)$  is a white Gaussian noise [1]-[3]. The main objective of image-de-noising techniques is to remove such noises while retaining as much as possible the important signal features. One of its main shortcomings is the poor quality of images, which are affected by speckle noise. The existence of speckle is unattractive since it disgraces image quality and affects the tasks of individual interpretation and diagnosis. An appropriate method for speckle reduction is one which enhances the signal-to-noise ratio while conserving the edges and lines in the image.

## 3. REVIEW OF SPECKLE FILTERS

which enhances the signal to noise ratio while preserving the edges and lines in the image. To address the multiplicative nature of speckle noise, Jain developed a homomorphic approach, which is obtained by taking the logarithm of an image, translates the multiplicative noise into additive noise, and consequently applies the Wiener filtering.

Recently many techniques have been purposed to reduce the speckle noise using wavelet transform as a multi-resolution image processing tool. Speckle noise is a high-frequency component of the image and appears in wavelet coefficients. One of the widespread method which is mainly exploited for speckle reduction is the wavelet shrinkage method. A comparative study between wavelet coefficient shrinkage filter and several standard speckle filters that are being largely used for speckle noise suppression which shows that the wavelet-based approach is deployed among the best for speckle removal [7][8].

## 4. SPECKLE FILTERING

In speckle filtering a kernel is being moved over each pixel in the image and applying some mathematical calculation by using these pixel values under the kernel and replaced the central pixel with calculated value. The kernel is moved along the image only one pixel at a time until the whole image covered. By applying these filters smoothing effect is achieved and speckle noise has been reduced to certain extent [9].

**4.1 Median filter [3]:** The best known order-statistics filter is the median filter in image processing. The median filter is also the simpler technique and it also removes the speckle noise from an image and also removes pulse or spike noise [1]-[3].

**4.2 Lee filter [10]:** The lee filter is basically used for speckle noise reduction. The lee filter is based on the assumption that the mean and variance of the pixel of the interest is equal to the local mean and variance of all pixels with in the moving kernel. The formula for the lee filter for speckle noise reduction is given as

$$R'(t) = I(t)W(t) + I'(t)(1-W(t))$$

$$\text{Where } W(t) = 1 - \frac{c^2 u}{c^2 I(u)} \quad \text{And}$$

$$C_u = \frac{\sigma_u}{u}, \quad C_I(t) = \frac{\sigma_I(t)}{I(t)}$$

are the various coefficients of the speckle  $u(t)$  and the image  $I(t)$ , respectively.

**4.3 Kaun filter [11]:** In this filter given kaun et al., the multiplicative noise model is first transformed into a signal-dependent additive noise model. Then the MMSE criterion was applied to this model. The resulting filter has the same form as the lee filter but with the different weighting function which is given as

$$W(t) = \frac{1 - \frac{C_u^2}{C_I^2(t)}}{1 + \frac{C_u^2}{C_I^2(t)}}$$

Kaun filter is much better than the lee filter.

**4.4 The srad filter [13]:** SRAD filter is known as speckle reducing anisotropic diffusion. The SRAD can eliminate speckle without distorting useful image information and without destroying the important image edges. The SRAD PDE exploits the instantaneous coefficient of variation in reducing the speckle. The results which are given below tells the SRAD algorithm provides superior performance in comparison to the conventional techniques like lee, frost, kaun filters in terms of smoothing and preserving the edges and features.

#### 4.5 Wiener Filter

wiener2 lowpass-filters an intensity image that has been degraded by constant power additive noise. wiener2 uses a pixelwise adaptive Wiener method based on statistics estimated from a local neighborhood of each pixel. It estimates the local mean and variance around each pixel.

$$\mu = \frac{1}{MN} \sum_{n1, n2 \in \square} a(n1, n2) \dots \dots \dots 5$$

$$\sigma^2 = \frac{1}{NM} \sum_{n1, n2 \in \square} a^2(n1, n2) - \mu^2 \dots \dots \dots 6$$

where  $\square$  is the N-by-M local neighborhood of each pixel in the image A. wiener2 then creates a pixelwise Wiener filter using these estimates.

$$b(n1, n2) = \mu + \frac{\sigma^2 - v^2}{\sigma^2} (a(n1, n2) - \mu)$$

#### 4.6 Mutation Bacteria Foraging Optimization

In the first stage Wiener filter is used to remove the speckle noise. In the second stage, both the noisy and Wiener filter output images will be passed as search space variables in the BFO technique [15] to minimize errors due to differences in filtered image and noisy image. Bacterial Foraging Optimization with fixed step size suffers from two main problems

- I. If step size is very small then it requires many generations to reach optimum solution. It may not achieve global optima with less number of iterations.
- II. If the step size is very high then the bacterium reach to optimum value quickly but accuracy of optimum value gets low. Similarly, in BFO, chemotaxis step provides a basis for

local search, reproduction process speeds up the convergence, elimination and dispersal helps to avoid premature convergence. To get adaptive step size, increase speed and to avoid premature convergence, the mutation by PSO is used in BFO instead of elimination and dispersal event by equation 1.

$$\theta^i(j+1, k) = \theta^i(j+1, k) + r1 * C1(\theta^i(j+1, k) - \theta_{global})$$

$\theta^i(j+1, k)$  = Position vector of  $i$ -th bacterium in  $j$ -th chemotaxis step and  $k$ -th reproduction steps.

$\theta_{global}$  = Best position in the entire search space .The BFPfPSO follows chemotaxis, swarming, mutation and reproduction steps to obtain global optima.

**The step by step algorithm of BF-pfPSO is presented below:-**

Initialize Parameters  $p, S, Nc, Ns, Nre, Ned, Ped$  and

$C(i), i = 1, 2, \dots, S$ . Where,

$p$  = Dimension of search space

$S$  = Number of bacteria in the population

$Nc$  = Number of chemotaxis steps

$Ns$  = Number of swimming steps

$Nre$  = Number of reproduction Steps

$Pm$  = Mutation probability

$C(i)$  = Step size taken in the random direction

specified by the tumble

$P(i, j, k)$  = Position vector of the  $i$ -th bacterium,  $I$   $j$ -th chemotaxis step, in  $k$ -th reproduction step and in  $l$ -th elimination and dispersal step

**Step 1:** Reproduction loop:  $k = k + 1$

**Step 2:** Chemotaxis loop:  $j = j + 1$

a) For  $i = 1, 2, \dots, S$ , take a chemotaxis step for bacterium  $i$  as follows

b) Compute fitness function  $J(i, j, k, l)$

c) Let  $J_{last} = J(i, j, k, l)$  to save this value since we may find a better cost via a run.

d) Tumble: Generate a random vector  $\Delta(i) \in R^p$  with each element  $\Delta_m(i) \quad m = 1, 2, \dots, p$ , a random number on  $[-1 \ 1]$

e) Move: Let

$$\theta(j+1, k, l) = \theta^i(j, k, l) + c(i) \frac{\Delta(i)}{\sqrt{\Delta^T(i) \Delta(i)}}$$

f) Compute  $J(i, j+1, k, l)$

g) Swim

i) Let  $m = 0$  (counter for swim length)

ii) While  $m < Ns$  (if have not climbed down too long)

- Let  $m = m + 1$

If  $J(i, j+1, k, l) < J_{last}$  (if doing better),

Let  $J_{last} = J(i, j+1, k, l)$  and let

$$\theta(i, j+1, k) = \theta^i(j, k, l) + c(i) \frac{\Delta(i)}{\sqrt{\Delta^T(i) \Delta(i)}}$$

and use this  $\theta^i(i, j+1, k)$  to compute the new  $J(j+1, k)$

- Else, let  $m = Ns$ . This is the end of the while statement

h) Go to next bacteria  $(i+1)$  if  $i \neq S$

**Step 3:** Update  $\theta_{pbest}(j, k)$  and  $\theta_{global}$

If  $j < Nc$ , go to step 3. In this case, continue chemotaxis, since the life of bacteria is not over.

**Step 4: Reproductions:**

- (a) For the given  $k$  and  $l$ , and for each  $i = 1, 2, \dots, S$ , let

$$J_{health}^i = \sum_{j=1}^{Nc+1} J(i, j, k)$$

be the health of bacterium  $i$ . Sort bacteria and chemotaxis parameter  $C(i)$  in order of ascending cost  $J_{health}$  (higher cost means lower health).

b) The  $Sr = S/2$  bacteria with the highest  $J_{health}$  values die and other  $Sr = S/2$  bacteria with the best values split.

#### Step 5: (New step): Mutation

For  $i = 1, 2, \dots, S$ , with probability  $P_m$ , change the bacteria position by pffSO.

Step 6: If  $k < N_{re}$ , go to step 2. We have not reached the specified number of reproduction steps. Therefore, we have to start the next generation in the chemotaxis loop.

The mean square error expressed in equation (7) between the noisy image and the wiener filter image has to be used as cost function in Mutation based bacterial Foraging technique to optimize the peak signal to noise ratio.

$$\text{Error} = \frac{1}{MN} \left[ \sum_{i=1}^M \sum_{j=1}^N z(x, y) - p(x, y) \right]^2 \dots\dots 7$$

Where MN is the size of the both noisy image and wiener filtered image. Performance of the MBFO technique is evaluated based on the Peak Signal to Noise Ratio (PSNR) and Mean Absolute Error (MAE) given by [10].

$$\text{PSNR} = 10 \log_{10} \frac{255^2}{\frac{1}{MN} \sum_{i=1}^M \sum_{j=1}^N (f'_{ij} - f_{ij})^2} \dots\dots\dots 7$$

$$\text{MAE} = \frac{1}{MN} \sum_{i=1}^M \sum_{j=1}^N (f'_{ij} - f_{ij})^2 \dots\dots\dots 8$$

Where  $f'_{ij}$  and  $f_{ij}$  represents the pixel value of restored image and original image respectively.

#### 4. EXPERIMENTAL RESULTS

The input image samples are considered from JAFFE database. a noisy face image of speckle noise is passed as an input for the system.

Wiener filter has been used to remove the noise and Mutation based bacteria Foraging optimization has been used to remove the remaining noise after applying the wiener filter. Applying the Speckle noise with mean and variance varying from 0.05 to 0. on all the images of the JAFFE face database. Figure 1 shows the sample of image database. Figure 2 shows the noisy image with variance 0.9. Figure 3 shows the restored image using Wiener filter.

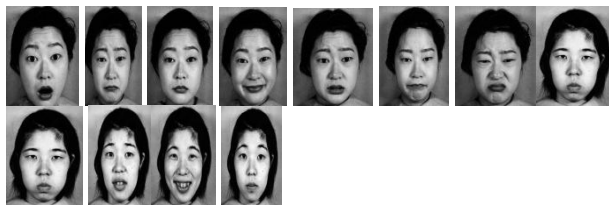


Fig -1 Sample images from JAFFE Database



Fig-2 Noisy Image



Fig-3 Restored Image

#### 5. CONCLUSION

In this paper we present human facial emotion detection in noisy environment. Wiener filter is used to remove the noise. Results shows that the noises are not removed properly so for removing the remaining noise Mutation based bacteria Foraging optimization techniques has to be used.

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