# Blind Source Separation and Genetic Algorithm for Image Restoration

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***Abstract*-Digital images often suffer from point spreading or blurring from both known and unknown filters or point spread functions. The sources of degradation can be lens point spreading, misfocus, motion, and scattering in case of x-ray images or atmospheric turbulence. Therefore a digital image can suffer blurring from a single or an combination of various point spread functions, for example many images suffer from lens out of focus blur because of manufacturing limitations or satellite/aerial images suffer from lens focus and atmospheric turbulence etc. The obvious requirement of an imaging system is to reproduce an image that is as close to original as possible. Most existing image restoration methods uses blind deconvolution and deblurring methods that require good knowledge about both the signal and the filter and the performance depends on the amount of prior information regarding the blurring function and the signal. Often an iterative procedure is required for estimating the blurring function such as Richardson-Lucy method and is computational complex and expensive and sometime instable. This paper presents a blind image restoration method based on techniques of blind signal separation (BSS) in combination with the genetic algorithm for parameters optimization. The method is not only simple but also requires little priori knowledge regarding the signal and the blurring function.**

## I. INTRODUCTION

Digital images generally suffer from degradation due to imperfections in the imaging and capturing process; therefore recorded image is invariably a degraded version of the original image. For instance, satellite/aerial images often suffer degradation from atmospheric turbulence and common images may have lens defocusing problems.

In addition to these blurring effects, noise always corrupts any recorded image. It can be introduced into the system by the creating medium or by the recording medium or simply because of the measurement error. Undoing these imperfections is crucial for many image processing tasks. During reconstruction process, the characteristics of the degrading system and the noise are assumed to be known a prior. However, these information may not be available for image formation, therefore goal of reconstruction requires not only restoration of image but also estimation of the blurring parameters from the degraded image; the process is often referred as blind image deconvolution.

Blind deconvolution is not a new area as quite extensive efforts by researchers exist in this field. Like [4] gives a adaptive guassian blind deconvolution method for satellite images. The technique is robust and gives vary satisfying results on high-resolution satellite data. However, the method is limited in the sense that it is for guassian deblurring of satellite images only.

In [7] an algorithm for blind restoration of blurred and noisy images has been proposed; the technique involves two processing blocks, one for denoising based on singular value decomposition and compression filtering and the other for deblurring based on a double regularization technique. It has been demonstrated that the method is fairly effective in restoring severely blurred and noise corrupted images, without prior knowledge of either the noise or image characteristics. This technique, although quite useful; is not completely blind. It requires prior information on the image degradation function to implement the algorithm.

An exhaustive list on the existing methods for image restoration and identification can be found in [5]; and a few more methods are elaborated in [7,8,12]. However, the mentioned techniques are limited in the sense that these are either domain specific i.e. for a particular category of images or particular type of degrading function or simply they require some prior knowledge about the point spread function (PSF), image or the noise. The motivation of this research is to apply an efficient and effective method, to perform complete blind deblurring and restoration of noisy and blurred images..

The proposed deblurring and denoising method is unique in the sense that it requires no prior knowledge about image, noise and the blurring function. As mentioned earlier that there could be many possible degradation functions such as misfocus, motion or atmospheric turbulence, etc. The proposed method can be extended to cater degradation caused by any kind of blurring function.

## II. NONGAUSSIANITY BASED IMAGE DEBLURRING

The blurring of images is modelled as the convolution of an original image with a 2-D point spread function (PSF) b(n1; n2).

$$x(n_1, n_2) = f(n_1, n_2) \otimes b(n_1, n_2) + n(n_1, n_2) \quad (1)$$

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where $\otimes$ is the convolution operator. In Equation (1), the degraded image x(n1; n2) is the result of convoluting the original image f(n1; n2) with the PSF b(n1; n2) and then adding noise n(n1; n2).

The interpretation is that if the original image f(n1; n2) would consist of a single intensity point or point source, this point would be recorded as a spread-out intensity pattern b(n1; n2), hence the name point-spread function. It is worth noticing that the PSFs under consideration here are not functions of the spatial location, i.e., they are spatially invariant. Essentially this means that the image is blurred in exactly the same way at every spatial location. Hence an obvious solution to the problem is to find a way to deconvolute the signal in a manner that one relies on as little information as possible about the image, noise and the blurring function.

In blind deconvolution, a convoluted version x(t) of a scalar signal f(t) is observed, without knowing the signal f(t) or the convolution kernel [8,10,11]. The problem is then to find a separating filter h so that f(t)=h(t)*x(t). The equalizer h(t) is assumed to be a FIR filter of sufficient length, so that the truncation effects can be ignored. In order to solve the problem in full generality, one must assume that the signal s(t) is non-Gaussian, and use higher-order information [2,3].

Blind signal separation (BSS) is a technique that recovers a set of independent signals from a set of measured signals without a priori knowledge of the sources. The basic concept behind is that the mixed signals are statistically more dependent than their original sources and basic working methodology behind such a scheme is looking for non-gaussianity in the recovered signals. The output of a linear system usually has a gaussian output, because of the 'Central Limit Theorem'. Hence a BSS algorithm tries to find a solution that maximizes the "non-gaussianity" of the recovered signal, a suitable solution for blind deconvolution too.

The Central Limit Theorem states that, 'the sum of several independent random variables, such as those in x, tends towards a Gaussian distribution'. The Central Limit Theorem implies that if we can find a recombination of the measured signals in 'X' with minimal gaussian properties, then that signal will be one of the independent signals. In order to do this some means to measure nongaussianity is required.

Kurtosis is the classical method of measuring nongaussianity. When data is preprocessed to have unit variance, kurtosis is equal to the fourth moment of the data. In an intuitive sense, kurtosis measures how "spikiness" of a distribution or the size of the tails. Kurtosis is extremely simple to calculate, however, it is sensitive to outliers in the data set.Mathematically kurtosis is defined as

$$\mathrm{kurt}(y)=E\{y^4\}-3(E\{y^2\})^2 \tag{2}$$

or, in cases where y has unit variance, $\mathrm{kurt}(y)=E\{y^4\}-3$. In other words, kurtosis is a normalised version of the fourth moment $E=\{y^4\}$.

The other measure used for measuring nongaussanity is negentropy. Negentropy is based on the information theoretic quantity of differential entropy. Negentropy is simply the differential entropy of a signal y, minus the differential entropy of a gaussian signal with the same covariance of y.

$$J(y)=H(y_{gauss})-H(y) \tag{3}$$

Negentropy is always positive and is zero if and only if the signal is pure gaussian. It is stable but difficult to calculate. The non-gaussianity measures kurtosis and negentropy have been applied in this study for finding independency and nonguassianity in the proposed image deblurring process.

The blurring process of images produces correlation between the adjacent points of the signal thus making the signal more guassian than the original ones, as outlined by 'Central Limit Theorem'. Further stronger the blurring more the degraded signal moves towards guassian.. Figure 1 highlights this fact with guassianity analysis for blurred (of various scales) Barbra and washsat images. The images become more guassian as a results the blurring. The stronger the blurring the more guassian the images become.

If one wishes to recover the original signal then it would be the one, which has minimum guassian properties. Therefore a filter that maximises the

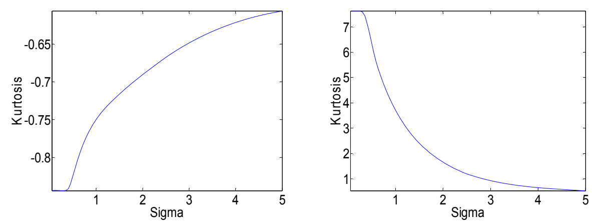


Fig. 1. Guassianity analysis for Barbra (left) and washsat (right) images blurred by guassian PSF with increasing value of sigma.

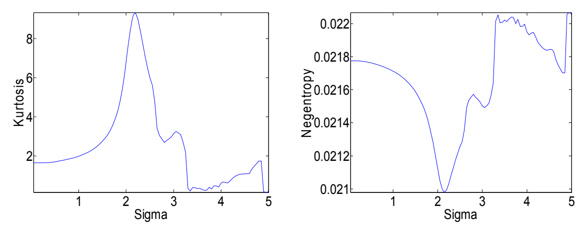


Fig. 2. Non-Guassianity analysis (kurtosis-left, & negentropy-right) for washsat image for guassian deblurring. Kurtosis/negentropy maximizes/minimises on sigma value on which it was blurred.

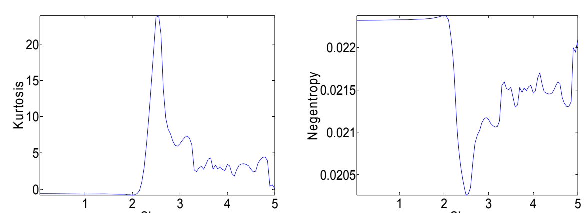


Fig. 3. Non-Guassianity analysis (kurtosis-left, & negentropy-right) for Barbra image for guassian deblurring. Kurtosis/negentropy minimises /maximises on sigma value on which it was blurred.

nonguassianity of the recombined degraded signal would be the inverse of the filter that has produces the blurring in the first place. Once the degradation is estimated then only thing left is to deconvolute the filter with corrupted signal to restore the original signal. Figure 2 and 3 demonstrate the nonguassianity measures of two images (Barbra and washsat) after applying deblurring on various values of sigma. Both signals have been blurred with guassian point spread function of sigma value 2. The blurred image was inverse filtered with various values of sigma and its kurtosis/negentropy) was calculated and shown in the figures. Thus value of sigma on which system is optimized is the actual value on which the blurring was performed in the first place.

## III. Proposed Method

Here we present a blind image de-convolution approach using independent component analysis and genetic algorithms. The method makes use of the difference between blurred (correlated) and (un-blurred) original images, actual image can be achieved using any non-gaussianity measure, i.e. kurtosis and negentropy as BSS uses to separate the signals. Here non-gaussianity measure (kurtosis) is used to differentiate between the correlated (blurred image) and the uncorrelated image; The restored image is more independent (uncorrelated) than the blurred image. The mentioned cost function is used to optimize the estimated PSF b'(n1; n2) by a simple genetic algorithm in an iterative manner. The operation is conducted in the frequency domain. The approach is computationally simple and efficient. The results and performance are given in the following figures and table. The whole process can be summarised in following steps:

- Initialize the genetic algorithm parameters, population size, crossover rate, mutation rate, etc.
- Calculate the kurtosis of the blurred image and Fourier coefficients of the blurred image.
- Perform first iteration and for different values of the optimizing parameter (i.e. sigma in case of gaussian point spread function); find the restored image through inverse/wiener filtering in the spectral domain. Convert the image in spatial domain and calculate its kurtosis (i.e. fitness function) for different population samples.
- Generate the child population for next iteration by evolving from the parents on the basis of the fittest function, and optimize the fitness function in subsequent iterations (generations).

The proposed method is simple and easy to implement. The method is only applied for estimation of one parameter of the blurring filter like spread (sigma) of Gaussian blurring filter or length of motion in case of motion blur etc. Further different PSFs are applied for the blind deconvolution of the blurred images with and without noise.

## IV. Experimental Results

The proposed algorithm was tested on various images degraded with different degrading functions, first without noise. The genetic algorithm along with nonguassianity measure was used to find and fine-tune the blurring parameters of the degrading function.

### *A. Atmospheric Turbulence Blur*

Atmospheric turbulence is a severe limitation in remote sensing. Although the blur introduced by atmospheric turbulence depends on a variety of factors (such as temperature, wind speed, exposure time), for long-term exposures the point-spread function can be described reasonably well by a Gaussian function:

$$b(x, y; \sigma) = C \exp\left( - \frac{x^2 + y^2}{2\sigma^2} \right) \tag{4}$$

Here sigma determines the amount of spread of the blur, and the constant *C* is to be chosen so that an energy conservation rule is satisfied. The proposed algorithm was applied for deconvolution of 2D singal (image) from guassian blurring. Figure 4 displays the results for the image, which was blurred with guassian PSF of spread '2, the proposed method estimated the blurring parameter (estimated sigma=2.33) and performed the deblurring.

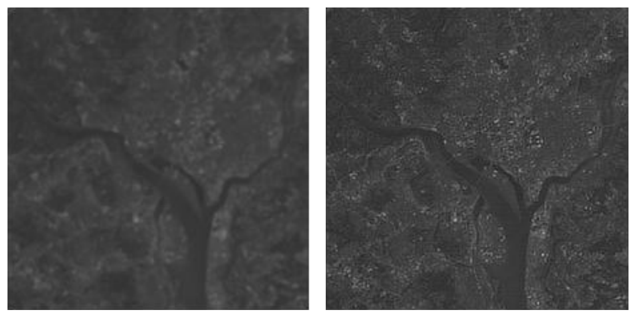

Fig. 4. Degraded image with guassian blurring of sigma=2 and restored image with proposed method where estimated sigma=2.33.

### *B . Uniform Out of Focus Blur*

When a camera takes a 3-D scene onto a 2-D imaging plane, some parts of the scene are in focus while other parts are not. If the degree of defocusing is large relative to the wavelengths considered, a geometrical approach can be followed resulting in a uniform intensity distribution. The spatially continuous PSF of this uniform out-of-focus blur with radius '*R'* is given by:

$$b(x, y; L, \varphi) = \begin{cases} \frac{1}{\pi R^2} & \text{if } \sqrt{x^2 + y^2} \le R^2 \\ 0 & \text{elsewhere} \end{cases} \tag{5}$$

The discrete version b$(n_1;\ n_2)$ is not easily derived, a coarse approximation is the following spatially discrete PSF:

$$b(n_1, n_2; R) = \begin{cases} \frac{1}{C} & \text{if } \sqrt{n_1^2 + n_2^2} \le R^2 \\ 0 & \text{elsewhere} \end{cases} \tag{6}$$

where *C* is a constant that must be chosen so that energy conservation law is satisfied. The approximation of (6) is incorrect for the fringe elements of the point-spread function. A more realistic PSF is shown in Figure 5. Next, Figure 6 displays the application of the algorithm on this type of burring with ‘uniform out of focus blur’ of radius ‘11’. Then the proposed method is applied to optimize the deblurring parameters using kurtosis and nonguassianity measures.

### C. LINEAR MOTION BLUR

Many types of motion blur can be distinguished due to relative motion between recording device and the scene

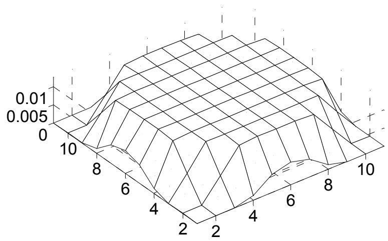


Fig. 5. PSF of uniform out of focus blur of radius ‘5’.

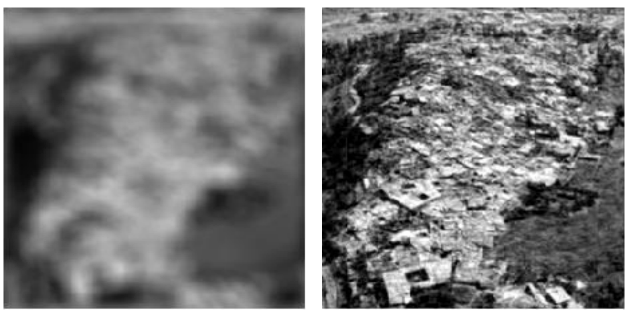

Fig. 6.Uniform out of focus blur image of radius ‘11’ and restored image with estimated radius of focus blur ’11.23’ respectively, for earthquake image.

When the scene to be recorded translates relative to the camera at a constant velocity *v*-relative under an angle of theta radians with the horizontal axis during the exposure interval, the distortion is one-dimensional. Defining the ‘length of motion’ by $L = v_{\text{relative}}\, t_{\text{exposure}}$. The PSF is :

$$b(x, y; L, \varphi) = \begin{cases} \dfrac{1}{L} & \text{if } \sqrt{x^2 + y^2} \le \dfrac{L}{2} \text{ and } \dfrac{x}{y} = -\tan\varphi \\ 0 & \text{elsewhere} \end{cases} \quad (7)$$

The discrete version is not easily captured in a closed form expression in general. For the special case that theta =0, an appropriate approximation is

$$b(n_1, n_2; L) = \begin{cases} \dfrac{1}{L} & \text{if } n_1 = 0, |n_2| \le \left[\dfrac{L-1}{2}\right] \\ \dfrac{1}{2L}\left\{(L-1) - 2\left[\dfrac{L-1}{2}\right]\right\} & \text{if } n_1 = 0, |n_2| = \left[\dfrac{L-1}{2}\right] \\ 0 & \text{elsewhere} \end{cases} \quad (8)$$

Fig.7.sows the point-spread function obtained with application of (8) for linear motion (horizontal) for length of 11 with zero angle with the horizontal direction.

Proposed method was tested to estimate the blurring parameter for subsequent deblurring of the image, in figure 8 and 9; results are displayed for the blurring and deblurring attempt of the algorithm with horizontal motion.

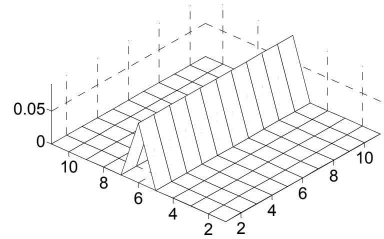


Fig.7. PSF of Linear motion blur of length ‘11’.

Fig. 8. Horizontal linear motion blur image of length ‘11’; restored with estimated length of linear blur ’11.55’.

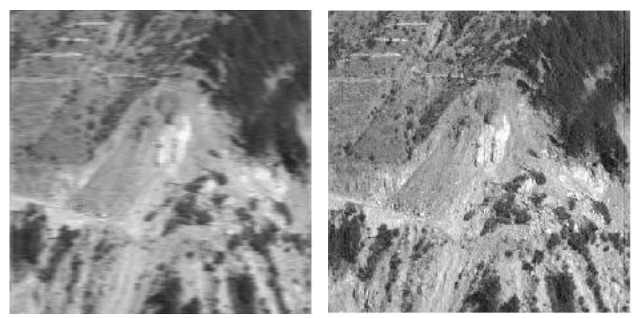

Fig. 9. Horizontal linear motion blur of earthquake balakot image of length ‘11’; restored with estimated length of linear blur ’11.6

### D.DEBLURRING AND DENOISING

The algorithm has also been extended to include the denoising. The blurred and noisy (additive white guassian noise) image becomes more guassian as compared to the original image (i.e. its kurtosis/ negentropy becomes guassian as a result of the bluring and adding noise). The wiener filtering is used to denoise and deblur the image; proposed algorithm is used to estimate the required parameters of the blurring PSF and the noise. Figures 10 and 11 show the comparison and Table 1 gives the PSNR comparison of this technique with Wiener Filter, Regularized Filter, Richardson Lucy method and blind Richardson Lucy method. The proposed technique outperforms both visually and quantitatively.

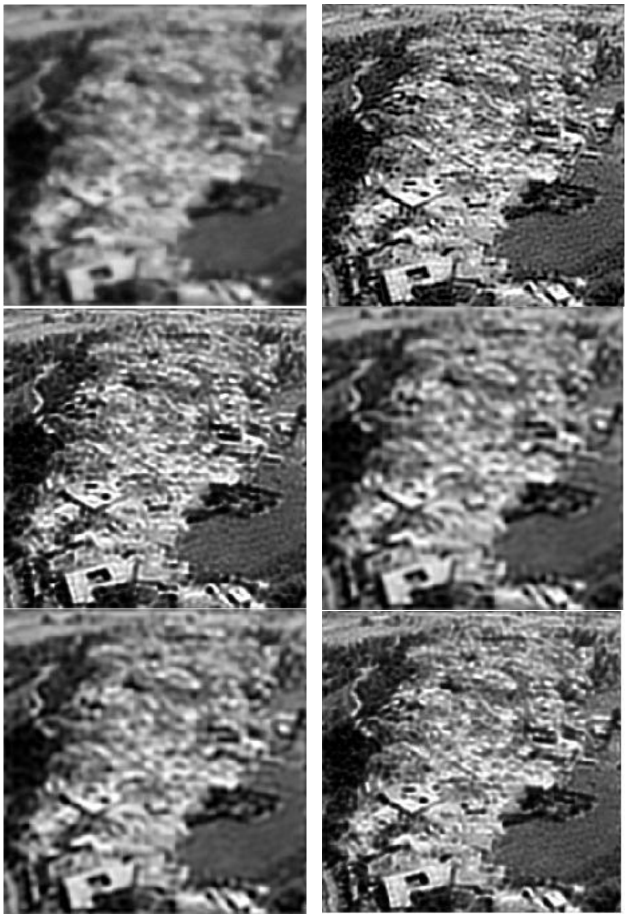

Fig. 10. Blurred images (top left), processed with proposed method (top right), processed with Richardson Lucy (middle left), processed with Regularized filter (middle right), processed with Wiener Filter (bottom left) and processed with Blind Rishardson Lucy method (bottom right).

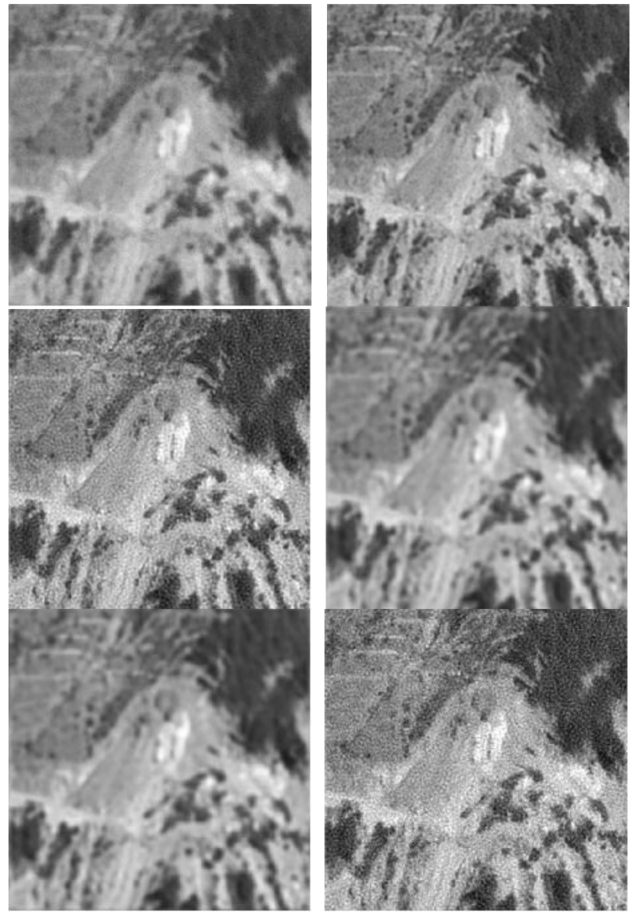

Fig..11. Blurred images (top left), processed with proposed method (top right), processed with Richardson Lucy (middle left), processed with Regularized filter (middle right), processed with Wiener Filter (bottom left) and processed with Blind Rishardson Lucy method (bottom right).

TABLE I
PSNR COMPARISON OF PROPOSED METHOD WITH OTHER TECHNIQUES FOR BALAKOT AND MUZAFFARABAD IMAGE

| PSNR (db) | | | | | | |
|---|---|---|---|---|---|---|
| | Blurred Image | Wiener Filter | Regularized Filter | Richardson Lucy | Blind Richardson Lucy | Proposed Method |
| bkot | 22.35 | 22.58 | 22.58 | 22.79 | 21.82 | 23.41 |
| mzrbad | 17.19 | 17.84 | 17.84 | 18.56 | 19.01 | 19.13 |

## V. DISCUSSION AND FUTURE WORK

The proposed method is simple and easy to implement in practice and most important of all, it is completely blind. The method has limitations; firstly as it is based on genetic algorithm it is iterative process for optimizing the cost function. As the image processing is done in frequency domain therefore it is bit computationally expensive. The fitness function is based on the kurtosis, which is prone to outliers, therefore can have convergence issue in some case. To alleviate the convergence issues, negentropy instead of kurtosis can be a suitable alternative as a fitness function in genetic algorithm. Future endeavors are to tackle noise and robustness against outliner as well as function optimization.

## VI. CONCLUSIONS

A new method based on nongaussianity measures of and the genetic algorithm for blind deconvolution and deblurring of images has been proposed. The method is conducted in spectral domain where genetic algorithm was used for optimizing the required parameters of the degrading function. The method does not require any a priori knowledge about the image and the blurring function. The proposed method has been tested on a number of images blurred with various PSFs with and without noise. The results indicate that the proposed method is able to deblur images effectively. A comparison with existing deconvolution methods shows the superior performance of the proposed method over others.

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