REAL-TIME ADAPTIVE FILTERING FOR NONSTATIONARY IMAGE RESTORATION USING GAUSSIAN INPUT

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Abstract

A new real-time adaptive filter algorithm is presented for the restoration of the images which are degraded by the Atmospheric turbulence or imaging systems. Filter model parameters of the proposed algorithm adaptively converge degradation model parameter in a given time duration. Then, a restoration filter is constructed using mentioned filter parameter. Considerable results have been obtained after the real-time restoration.

Keywords : Real-time adaptive filter, Gaussian model, Image restoration.

I. Introduction :

Image degradation based on imaging systems is an inherent property of image formation systems. This effect can be easily handled with the focus arrangement of the lenses. But, another degradation effect based on environmental factors can only be removed by using the image processing techniques[1] As known, a scenery can be visualized as an original from the short distance by using the well-focused imaging systems. Whereas, in the long distance, atmospheric turbulence between the camera and the scenery become an important degradation factor on image quality,because the atmospheric turbulence change from time to time and place to place and extensive variations of the parameters of degradation model can not be controlled during the imaging process. Although, automatic focus arrangement can partially compensate the effects of the Atmospheric turbulence during the real-time imaging, it is an inherent property of image formation systems.

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Many researchers use the remote sensing images for their research areas. For example, the Satellite images can be used for finding of crater hole caused by the meteor hit to the earth, finding of location of the archeological dig places or earth sources, plant cover and the crop estimation. Because of the effects of the Atmospheric turbulence, these images can not also contain enough information and some details can be lost. In other words, researchers can not obtain correct results from these images.Therefore, the remote sensing images must be handled by using the image processing techniques before they can not be presented to the researchers. This will be an important contribution for the above mentioned research working areas.
There are many methods handled in literature for the restoration problem[1-11]. Furthermore, iterative-adaptive filtering techniques have been effectively used in real-time restoration.
Adaptive filtering has been an active area of research since Widrow and Hoff proposed the least mean square (LMS) algorithm[12] in 1959. Adaptive filters have found many applications in areas of communication, signal and image processing such as echo cancellation[13], noise cancellation1[4], channel equalization1[5] and system identification1[6-17]. Among these applications, the adaptive finite impulse response (FIR) filter based on the LMS algorithms being widely used due to its ease of implementation. One known drawback of the LMS algorithm is that it has slow convergence when the eigenvalues of the input signal correlation matrix are spread widely[18].
Many sequential algorithms have been proposed to improve speed of convergence of the LMS adaptive FIR filter. Fundamentally, these algorithms can be classified into the stochastic gradient (SG) and the least squares (LS) types. One useful SG algorithm is the variable step (VS) algorithm[19] that utilizes a time-varying convergence factor for each of the filter coefficients. Nevertheless, VS algorithms are not still an optimum algorithm and the proper variable step parameters can be difficult to choose[20]. The LS algorithms[21-22] converge very fast under stationary signal conditions, but unfortunately very little is known about their convergence behaviors in non-stationary environments. Moreover, with the computer simulation results in Cowan's work[23], we can see that a LS algorithm, is not always better than the LMS and other algorithms for low signal-to-noise ratios and it is not necessarily the best choice as far as the non-stationary environments are concerned.
In this paper, we present an adaptive method for real-time restoration of the Atmospherically blurred satellite images. We use the edge information of the blurred image to estimate the blur function model parameters. Next chapters explain the proposed algorithm in detail.

II. Model Identification:

A scenery can be modeled in two dimensions such as:

$$X_1(n_1,n_2) = B_1(n_1,n_2)\, X_1{*}(n_1,n_2) \tag{1}$$

where $B_1(n_1,n_2)$ is coefficient matrix of original scenery $X_1{*}(n_1,n_2)$. Also, a blur model can be modeled as,

$$X_2(n_1,n_2) = B_2(n_1,n_2)\, X_2{*}(n_1,n_2) \tag{2}$$

where $B_2(n_1,n_2)$ is coefficient matrix of blur function $X_2{*}(n_1,n_2)$.
By combined equations of (1) and (2), we can obtain a real world degraded image model, as follows:

$$Y(n_1,n_2) = X_1(n_1,n_2) * X_2(n_1,n_2) + N(n_1,n_2) \tag{3}$$

Where, N is the additive noise and Y is the observed image respectively. Additive noise comes from the imaging system and its model parameters are known. So, it can be removed from the degraded image by using the some special restoration techniques such as wiener filter etc… before the restoration. So we can re-write the observed image as,

$$Y = X_1 * X_2 \tag{4}$$

As seen, the degradation given as a result of an observation has been obtained by convolution between an original scenery and a blur function.
It is supposed that, blur function given in equation (2) has statistically Gaussian distribution. But, in the most general condition, all blurring effects have Gaussian or normal distribution. The Atmospheric turbulence, the unfocused imaging systems, motion effects cause to blurring of the original image with a Gaussian distribution as follows,

$$b'(n_1,n_2)=\frac{1}{2\pi\sigma^2}e^{-\frac{(n_1^2+n_2^2)}{2\sigma^2}} \qquad (5)$$

Equation (5) is the filter model and it will be used in the real-time restoration of blurred image. Where, the variance with zero mean and the matrix size of the blur function are the critical parameters on the filter performance.

Experimental results show that if the matrix size could be arranged suitably in the algorithm, it becomes second important parameter for the real-time applications. In this condition, first, the matrix size is searched and then fixed for a certain period. Then, the algorithm searches the variance. At the end of the period, the blur matrix size is updated, if it is necessary.

In this work, the edge detection has been used for the estimation of the filter variance accordingly. As known, sharp transitions called as edge pixels in a blurred image are spread to the neighborhood pixels and the intensity levels of sharp transitions decrease or some of them completely loss all over the image. In this condition, its edge map has more little edge pixels than the original. So, we can say that, the edge map of an image gives an important information about the degradation.

By the way, to estimate the variance, first, edge map, which related on variance of blur function, is obtained from the blurred image. Then, a filter is constructed by using this variance and image is restored. New edge map is computed from the previously restored image. If the new edge map contain more edges than previous edge map, this variance will be actual. After the certain number of iterations, the best edge map gives the best filter model parameter that has been used for the designing of restoration filter.

Filtering can be easily handled in the Cepstrum domain [10-11] from the equation (4) such as,

$$Y' = X_1' + X_2' \qquad (6)$$

As seen, original scene and blur function are additive in Cepstrum domain. If, designed filter is $b(n_1,n_2)$, filtering in the Cepstrum domain is

$$Y' = X_1' + X_2' - h' \qquad (7)$$

Here, minimizing of the error between the blur function model parameters and the constructed filter model parameters provide to improvement of the quality in image.

After the calculation of the mathematical model of the filter, the parametric sensibility of the model has been realized as below.

- Parameters have been selected from the suitable model definition and required sensitivity for the filter design has been presented.
- A classification has given via the degree of effect of the filter parameters.
- Least significant filter parameter has only been updated after a given period for simplification
- The most significant parameter effected on the rightness of the model has been realized after the experimental observations.

III. The Real Time Adaptive Filter Identification Algorithm

Effects coming from the atmospheric turbulence or the other media can change from time to time or place to place and these changes cause the deviation of the filter model parameters and the degradation of the image quality. To overcome this problem, the filter parameters have been periodically updated and optimized after a certain time duration. If the actual filter coefficients can not close the previously constructed filter coefficients, the filter model parameters are re-arranged using the evaluation algorithm. Resulting parameters are the new coefficients for the filter model. Consequently, the filter model coefficients stay in an optimum value evenif environmental conditions are changed[32].

Figure-1 shows a block diagram of proposed model. where, x_i and y_i are the input and output variables of the system, y'_i is the model output, b and b' are the suitable parameters vector of model and filter, ε=y-y' is the difference error between the unmeasured random effect (ξ) and a real characteristic convergency error that comes from the computation of the filter model, $F(\varepsilon)$ is a function for evaluation of the error quantity and it can be written as,

$F(\varepsilon)=\varepsilon^2$ (8)

Output y of the filter (b) and the error ε is depend on some random variables such as x, b' and ξ. All of these effects make very complex to solve the problem. So, an optimization is necessary for computing the model (b) coefficients as written below,

$$S = M\{ F(\varepsilon) \}= M\{F[y(x, \xi, b) - y'(x,b')]\} \quad \rightarrow \quad \min_b \tag{9}$$

Where, M is the observation value that mathematically computed from the random y's. Consequently, the mathematical observations must be taken into the consideration for the S function. In that case of the minimization condition used in the computation of b can be written as the sum of the N values,

$$S_T = \sum_{i=1}^{N} F\{y(i) - y'(x(i), b\} \tag{10}$$

Where, N values of x_i vectors and y_i vectors must be computed for the evaluation of b as below,

$$b^{i+1} = b^i + \Delta b^i\,[y(i+1)\,;\,x(i+1)] \tag{11}$$

Where, b^{i+1} is the convergency vector of model coefficients in a given time duration (i+1) , Δb^i are the corrections depend on measurements along a period. Error computations are made by using the mean square error criteria.

Proposed algorithm can be explained step-by-step as below .

1. Read digitized image ($X(n_1,n_2)$),
2. Estimate the filter parameter called variance (σ^2) from the edge map of degraded image after 20 iterations steps,
3. Construct a restoration filter using the computed parameter in step (2) (filter model $b'(n_1,n_2)$ was given in equation (9)),
4. Compute the Cepstrum transform of filter and image,
5. Apply the designed filter to blurred image ,(X-b')
6. Compute the inverse Cepstrum transform of (6),
7. Repeat the same process from (4),
8. Apply another blurred image automatically for real time application and restore the new blurred image using steps 4,5,6,7
9. Re-estimate the filter parameter continuously and compare it with previous filter parameter.

If it remains under a critical error, go on restoration.

Else, refresh the filter parameter with new value.

IV. Results and Discussions

Adaptively converged real-time restoration algorithm has been tested by using the simulated and real world images. A simulated image has been handled to test the rightness of the algorithm. Then, it has been generalized to the real world satellite images.

Figure-2.a,b,c and d show the simulated blurred Tac Mahal image, edge map of (a), unsuitable restoration from (a) and edge map of (c) respectively. Note that, because of the blurring process, some detail information has lost and its edge map does not include more edges than the edge map of original image. Figure-2.e shows the correct restoration result and improvement in image quality considerable as given in table-1.

Figure-3.a, 4.a, 5.a and 6.a show some real world satellite images and 3.b, 4.b, 5.b,6.b show edge map respectively. Note that, some details of image are loss and they are not very clear. When we apply our algorithm to this image, improvements in detail information and edge map are very clear as shown in figure-3.c, 4.c, 5.c, 6.c. Experiments show that, only, original unblurred image has the most edge pixels on the edge map. Improvements in the image quality are considerable as given in table-1.

Performance of the real time adaptively converged filter is proportional to the improvement in the image quality. As shown in table-1, improvement in simulated Tac-Mahal image is very good,

because the original scene has only degraded by the blur function and there are not any other effects on the image.
But, in the real world images, there are some unmeasured observation noises such as ξ that effect the image quality. These effects have partially compensated by the real-time filter, but not all. As known, in a real world image, restoration error can not compute. Only, the improvement in image quality can be found and it can be compared with the simulated results for an interpretation.
Gaussian distribution is the most general condition and it includes the other distribution types. So, gaussian model has been used in the filter design in this work. But, because the gaussian distribution has three variable parameters (mean, variance and size of distribution (matrix size)), filtering problem becomes very complex. So, some filter parameters have been optimized for simplicity.
In this study, matrix size is fixed for certain time duration. In fact, the matrix size is depend on variance. But, if the matrix size can be chosen enough large, it becomes the second important parameter. So, the variance with zero mean is searched and then it is used in the filter algorithm. So the complexity of the problem decreases and the process time comes to very short.
Adaptively converged real time filter design algorithm need to 15 iterations. Algorithm gives a result approximately 3 minutes for the estimation of the blur parameters and approximately 15 second for the restoration.

V. Conclusions:

A new restoration algorithm has been proposed for the blurred images. Where existing moment information has been used for the construction of the adaptively converged real time filter.
Adaptation of the model to a new image is necessary if there is an incompatibility between existing model information and the output coordinates obtained from the model foresight. In other words, incompatibility error ε_y must not exceed the critical error ε_k . If the incompatibility error could not be exceed the boundary of $\varepsilon_y \leq \varepsilon_k$, then, the actual image can be restored using the previous filter model information. In this condition, re-arrangement of the filter model parameters are not necessary. Vice versa, if there is an incompatibility in the restoration, the model parameter must be re-arranged for increasing the rightness. In this way, adaptation of the model and evaluation of the model parameters has been periodically realized in a short time interval. For this aim, above mentioned information are measured in a given time duration which has basically been obtained from the technical observations, the opinions and the experiments.
Some experimental results from previously published algorithms with simulated images are given in table-2[7] and 3[6]. For comparison with our results. Note that, as shown in table-3, computation times of our method gives a result approximately as good as four times than previous works.
In future, this algorithm can be extended in the real time video processing problems by using the more speed microprocessor that have the parallel processing architecture.
This method is patent pending in 1998 by authors[32]

References

[1] J. S. Lim,"Two dimensional signal and image processing",Prentice Hall, 1990.
[2] C. Andrews, B.R. Hunt,"Digital image restoration",Prentice-Hall, Englewood-Cliffs, 1977.
[3] M. Cannon,"Blind deconvolution of spatially invariant image blurs with phase", IEEE Trans. on Acou.,speech and sig. Proc., v.ASSP-24, n.1, 1976, 58-63.
[4] M.K. Özkan, A.M. Tekalp, M.İ. Sezan,"POCS-Based restoration of space blurred images", IEEE Trans. on image proc., v.3, n.4, 1994, 450-454.
[5] Z. Telatar and Ö. Tuzunalp,"Edge estimation and restoration of gaussian degraded images", JIST, vol.42, n.4, 1998
[6] Scott, T.A., "Image restoration using generalized deterministic annealing", Digital Signal Proc., **7**, 94-104, (1997).
[7] S.J. Reeves and R.M. Mersereau,"Blur identification by the method of generalized cross-validation", IEEE Trans. on image proc., 1, 301 (1992).

[8] N.D.A. Mascarenhas, W.K. Pratt,"Digital image restoration under a regression model", IEEE trans. circuit and systems, CAS-22, 1975, 252-266.
[9] K. Rank, R. Unbehauen,"An adaptive recursive 2-D filter for removal of Gaussian noise in images",IEEE Trans. on image proc.,v.1,n.3, 1992, 431-436.
[10] M.G. Kang, A.K. Katsaggelos,"Simultaneous multichannel image restoration and estimation of the Regularization parameters",IEEE Trans. on image proc., v.6, n.5, 1997, 774-778.
[11] J.K. Lee, M. Kabrisky, M.E. Oxley, S.K. Rogers, D.W. Ruck,"The complex Cepstrum applied to two-dimensional images", Pattern Recognition, v.26, n.10, 1993, 1579-1592.
[12] Widrow, B. and M.E. Hoff, Adaptive switching circuits, IREWESCON Conv.Rec., 4, 96-104, (1960)
[13] Verhoecks, N.A.M, V. Elzen, F.A.M. Snijders, and P.J. van Gerven,"Digital echo cancellation for baseband data transmission",IEEE Trans. Acoust. Speech,signal Proc., ASSP-27, 768-781, (1979)
[14] Widrow, B., "Adaptive noise canceling: Principles and applications", Proc. IEEE, 63, 1692-1716, (1975)
[15] Widrow, B., J. McCoal, M. Larimore and C. Johnson, "Stationary and nonstationary learning characteristics of the LMS adaptive filter", Proc. IEEE, 69, 1151-1162, (1976)
[16] Sondhi, M.M. and D. Mitra, "New results on the performance of a well-known class of adaptive filters", Proc. IEEE, 69, 1583-1579, (1976)
[17] Haykin S, Adaptive filter theory, Englewood Cliffs N,J., Prentice Hall, 1986
[18] Harris, R.W., D.M. Chabries and F.A. Bishop,"A variable step (VS) adaptive filter algorithm", IEEE Trans. Acoust. Speech Signal Proc., ASSP-34, 309-316, (1986)
[19] Soo, J.S., K.K. Pang, "A multistep size (MSS) frequency domain adaptive filter", IEEE Trans. Signal Proc., 39, 115-121, (1991)
[20] Ljung, L, M. Morf and D.D. Falconer, "Fast calculation of gain matrices for recursive estimation schemes", Int. J. Contr., 27, 1-19, 1978
[21] Falconer, D.D. and L.Ljung, "Application of fast Kalman estimation to adaptive estimation", IEEE Trans. Comm., COM-26, 1439-1445, (1978)
[22] Cioffi, J.M. and T. Kailath, "Fast recursive least squares transversal filters for adaptive filtering", IEEE Trans. Acoust. Speech, Signal Proc., ASSP-32, 304-337, (1984)
[23] Cowan, C.F.N., "Performance comparison of finite linear adaptive filters", Proc. IEEE, 134, 211-216, (1987)
[24] Mathews, V.J. and Z. Xie, "A stochastic gradient adaptive filter with gradient adaptive step size", IEEE Trans. on sig. Proc., **41**, (1993).
[25] Anderson, B.D.O. and J.B. Moore, Optimal filtering , Prentice-Hall, 1979.
[26] Hubing, N.E. and S.T. Alexander,"Statistical analysis of initialization methods for RLS adaptive filters", IEEE Trans. on Sig. Proc., **39**, 1793-1834, (1991).
[27] Regalia,P.A., "Numerical stability issues in fast squares adaptation algorithms", Opt. Eng., **31**, 1144-1152, (1992).
[28] Honig, M.L. and D.G. Messerschmitt, Adaptive filters:Structures, algorithms and applications, Cluwer, New York, 1984.
[29] Astrom, K.J. and B. Wittenmark, Adaptive control, Addison Wesley, New York, 1988.
[30] Widrow, B. and S.D. Stearus, Adaptive signal processing, Prentice-Hall, Englewood Cliffs, NJ, 1985.
[31] Bellanger, M.G., Adaptive digital filters and signal analysis, New York Marcel De. Inc.,1987.
[32] Abilov, A. O.Tuzunalp, Z. Telatar, On-line image sensing system and method, Registered by Turkish patent institute (reg. number: 97/01001), 1998.

Table-1. Restoration results on simulated and real world images.

Images	Real Variance	Estimated Variance	Blur Kernel	MSE in Blurred Image	MSE in Restored Image	Improvement in Image Quality (dB)
Fig.-2	4.01	4	5	461.77	1.78	50.1 (Simulated)
Fig.-3	Unknown	2	15	-----	----	20.76 (HST)
Fig.-4	Unknown	6	15	-----	----	24.20 (HST)
Fig.-5	Unknown	2	15	-----	----	20.27 (HST)
Fig.-6	Unknown	5	15	-----	----	29.24 (HST)

Table-2. Restoration results from previous works

Methods	Real Variance	Estimated Variance	Blur Kernel	MSE
GCV	4	4.03	5	198.4
ML	4	4.08	5	159,67

Table-3. Comparision for computation times

Real-time Methods	MSE	Execution time (hh:mm:ss)
Our method	461.77	00:03:20 (on 90MHz Pentium-for figure-1)
GDA	410.2	00:13:31 (on Sun sparc Ultra-1)
SD	474.1	02:16:21 (on Sun sparc Ultra-1)

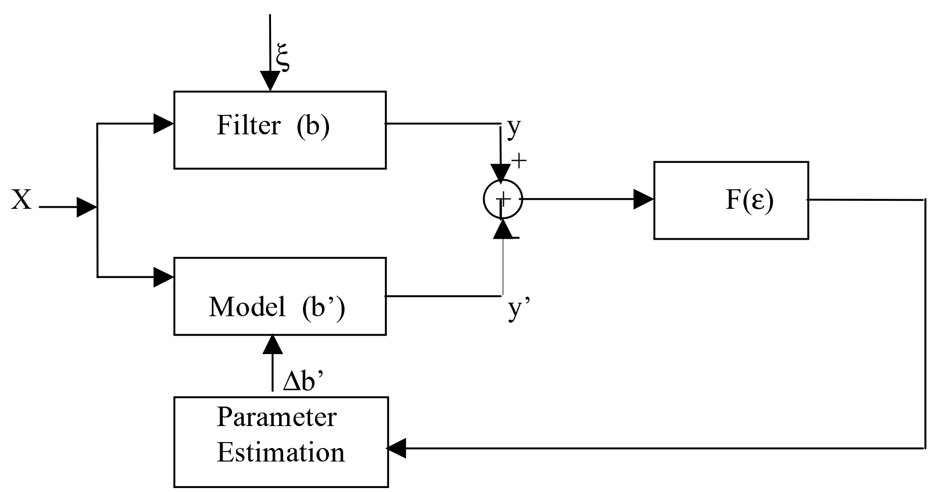

Figure- 1. Real Time Adaptive filter identification algorithm

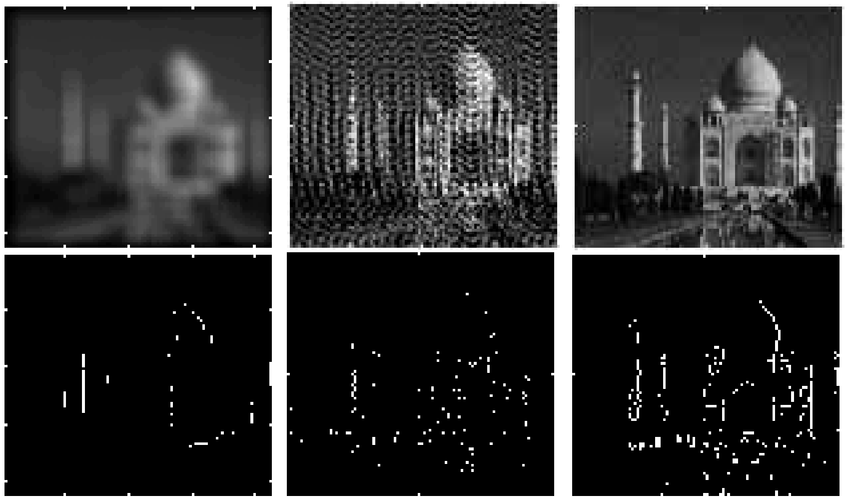

Figure-2. a. Blurred Tac Mahal image with variance 8 matrix and kernel 15 (left above)
b. Edge map of (a). (left below), c. Restored image by filter that has not been estimated correctly from the degraded image (variance 3) (middle above).
d. Edge map of (b) (middle below), e. Resulting image from (a). (right above)
f. Edge map of result of iterations. (right below)

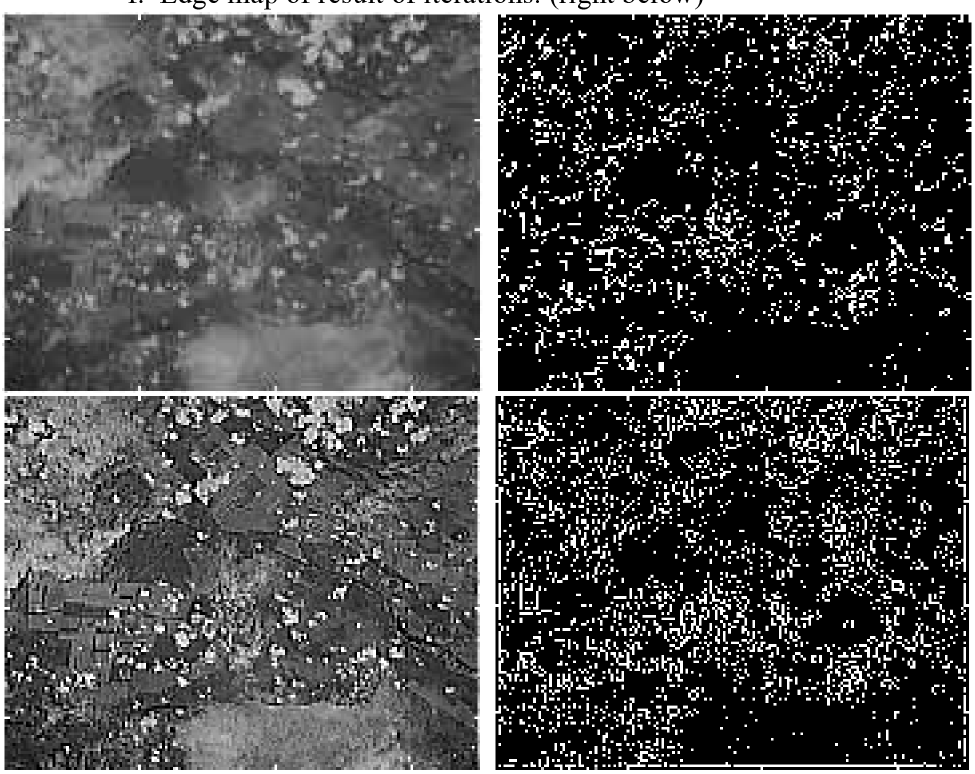

Figure-3.a. A real world HST image(left above), b. Edge map of (a) (right above)
c. Restored image from (a) (left below), d. Edge map of (c) (right below)

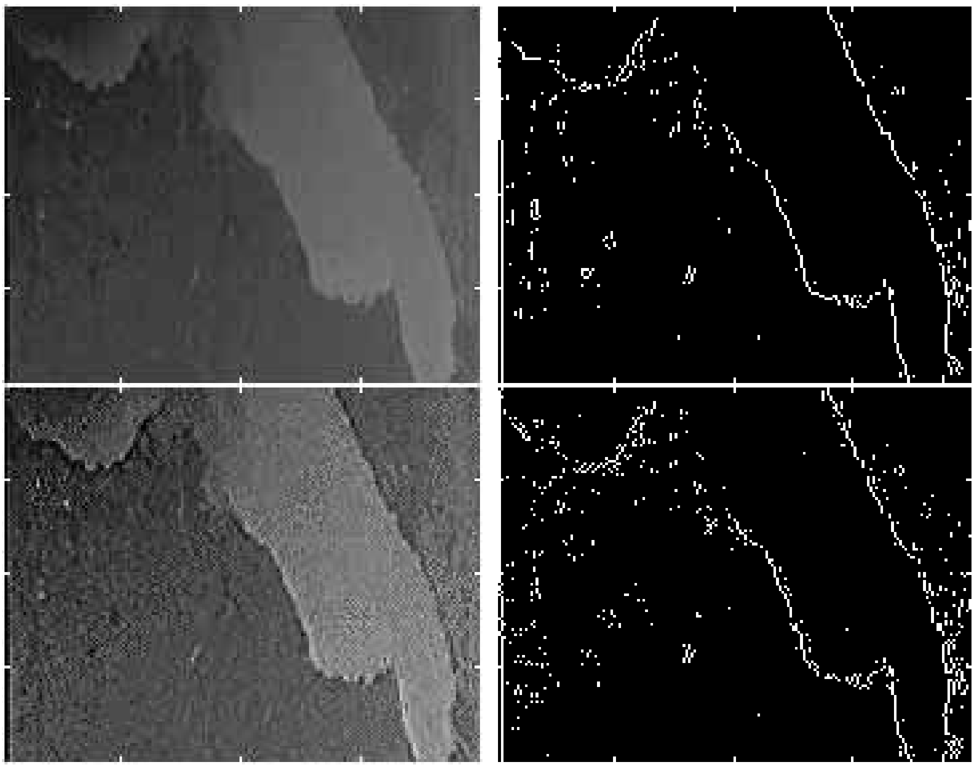

Figure-4.a. A real world HST image(left above), b. Edge map of (a) (right above)
c. Restored image from (a) (left below), d. Edge map of (c) (right below)

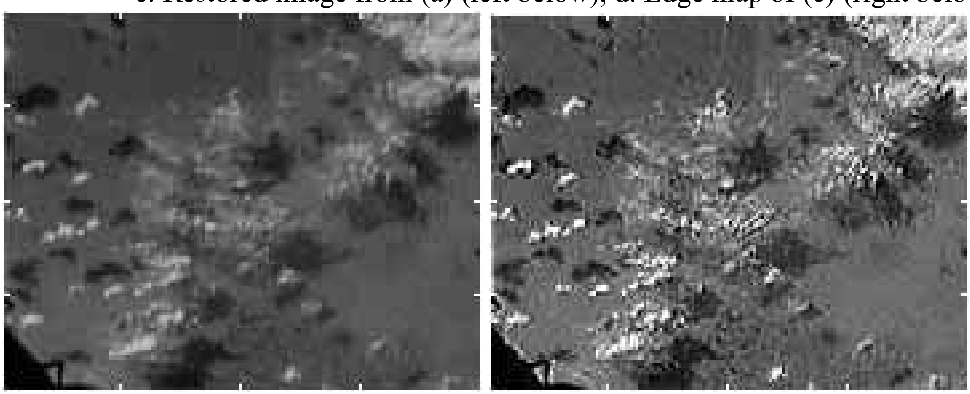

Figure-5.a. A real world HST image(left), b. Restored image from (a) (right)

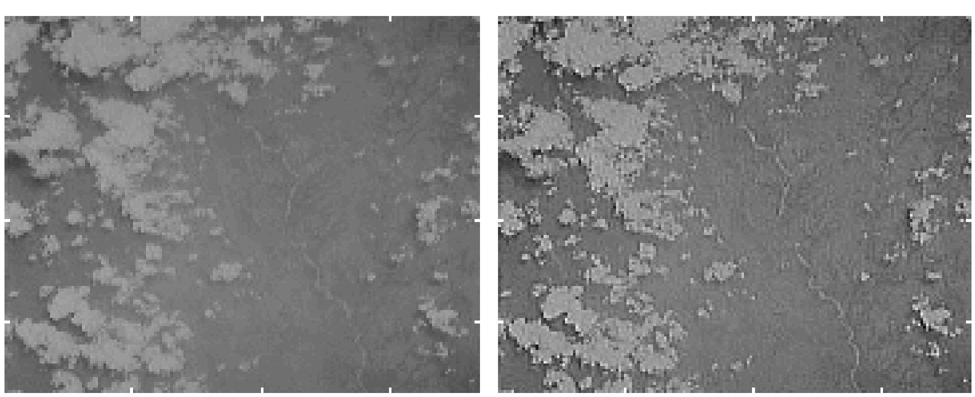

Figure-6.a. A real world HST image(left), b. Restored image from (a) (right)