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ON-LINE MODEL ADAPTATION FOR ALGORITHMIC FILTER CONTROLLER OF IMAGES

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ABSTRACT

A real-time adaptive filter controller algorithm is presented in order to estimate the blur parameter and remove degradation effects from blurred images. The presented algorithm estimates the degradation model parameters of the observed image in a certain period of time. Then, the filter parameters are held in a stable state within a critical error tolerance. If the error exceeds the critical tolerance, the estimated filter parameters are automatically updated in the restoration process. The algorithm yields considerable improvements in quality of the restored images and low computation time for the restoration process compared with the other estimation based restoration methods. The algorithm has been tested by different simulated and real-world images.

KEYWORDS

On-line model adaptation, Adaptive filter controller, Gaussian model, Image restoration

1. INTRODUCTION

Atmospheric turbulence, relative motion, improperly focused imaging systems among other artifacts affect the performance quality of real world images and make image detection more difficult. Many researchers use these images for their research areas. For example, satellite images can be used for locating a crater hole caused by the meteor or for finding location of the archeological excavation sites or natural resources, plant cover, crop estimation and so forth. Here, degraded images can not contain enough detail information for such purposes, because of the effects of atmospheric turbulence. Furthermore, the observations may have been obtained by the same sensor at different times and places. In this sense, the precise impulse response causing the blur effect for each recorded image can not be known and different blur effects contribute negatively over the images. Consequently, these type degraded images must be handled by using image processing techniques before they may be interpreted further. But, the problem in real time is to make reestimating and updating the restoration filter parameters for each image, because the imaging is a non-stationary process that has mostly been handled by using an adaptive methodology yielding considerable improvement on image quality.

In recent years, many adaptive iterative restoration schemes including blur estimation or identification methods have been proposed for the restoration problem. An adaptive iterative method [1,3,9,17,18] based on estimation of blur parameters was proposed to restore blurred images and patented for real-time applications in 1998 by the authors [2]. Other contributions include the estimation of image blur with edge features [8], Blind identification of blurred image under different input blur scenarios (multiple blur input) for perfect image restoration [4], the projections onto convex sets (POCS) [12] based on blur identification for space varying blurred images, the generalized cross validation method [14] (GCV) in identifying optimal smoothing parameters for image restoration, the approximate inverse preconditioning method [11] to solve the deconvolution problem of earth based star image, and the generalized deterministic annealing (GDA) and steepest descent methods (SD) as regularization approaches [6,7,15,16] were proposed to contribute the restoration problem in recent years.

This work concerns mainly solving the restoration problem in real time. The technique developed here follows an adaptive iterative scheme to estimate the filter model parameters and then restores each image using the updated filter coefficients at the end of the given period. This paper is organized as follows. In section 2., we discuss the general image degradation model and give our filter concept. In section 3., we represent an on-line adaptive filter controller realization. In section 4., we represent the on-line restoration algorithm. In section 5, we test our algorithm by synthetically blurred images and real world images and discuss the results. Finally, section 6 provides some concluding remarks.

2. MODEL DISCUSSION

The regression equation showing the relation between the input and the output of a general system can be taken into consideration for statistically modeling and solving the system. Here, the general model equation representing relation between output signal $\overline{Y}$ and input signal $\overline{X} = (x_1, x_2, ..., x_k)$ can be obtained from observations and measurements, as follows:

$$\overline{Y} = y + \xi = f(\overline{X}) + \xi \qquad (1)$$

Here, ξ is a random noise signal whose the statistical characteristics are given as:

- statistically independent from $\overline{X}$,
- it has centralized and limited dispersions,
- it is ergodic.

Here, $f(\overline{X})$ is an operator which accounts for the statistical dependence between $\overline{Y}$ and $\overline{X}$. Then, the regression equation from (1) can be written as,

$$y = f(\overline{X}) = b_0 + \sum_{i=1}^{n} b_i x_i + \sum_{\substack{i,j=1 \\ i \neq j}}^{n} b_{ij} x_i x_j + \sum_{i=1}^{n} b_{ii} x_i^2 \tag{2}$$

where y is the output variable, x_i and x_j are suitable input variables, and b_0, b_1, b_{ij} and b_{ii} are real coefficients obtained from the measurements and there is no correlation between b_i's as the equation (2) is ergodic. There are some difficulties in obtaining the parameters of equation (2) due to the effects of unmeasurable input variables, the stochastic characteristics of process, the correlation between measured and unmeasured effects and the information errors of input and output.

If the Equation (2) is expressed as linear model in matrix form:

$$Y = X_B \tag{3}$$

where, X is a diagonal matrix of input values, Y is a column matrix of output variables and B are the unknown coefficients of the model. Then the least-squares solution for B is given by,

$$B = (X^T X)^{-1} X^T Y \tag{4}$$

or the covariance matrix of the estimated coefficients B

$$\mathrm{cov}(B) = \sigma^2(Y)\left[X^T X\right]^{-1} = \begin{vmatrix} \sigma^2(b_0) & \mathrm{cov}(b_0 b_1) \ldots\ldots & \mathrm{cov}(b_0 b_n) \\ \mathrm{cov}(b_1 b_0) & \sigma^2(b_1) \quad \ldots\ldots & \mathrm{cov}(b_1 b_n) \\ \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot \\ \mathrm{cov}(b_n b_0) & \mathrm{cov}(b_n b_1) \ldots\ldots & \sigma^2(b_n) \end{vmatrix} \tag{5}$$

Matrix given in (5) includes the information related to the statistical properties of the model where, the diagonals show dispersions of regression coefficients and cov(b_i, b_j)'s show correlation moments (covariance evaluations) between coefficients b_i and b_j.

The statistical dependency expressed by the linear regression equations can be applied to two dimensional signal processing. In this sense, we can model a scene in two dimensions such as:

$$x_1(n_1, n_2) = b_1(n_1, n_2) x_1'(n_1, n_2) \tag{6}$$

where $b_1(n_1, n_2)$ is the regression coefficients of original data $x_1'(n_1, n_2)$. Also, the blur model is,

$$x_2(n_1, n_2) = b_2(n_1, n_2) x_2'(n_1, n_2) \tag{7}$$

where $b_2(n_1,n_2)$ is a regression coefficient of the blur data $x_1'(n_1,n_2)$ having Gaussian distribution. Then, according to Equations (6) and (7), a real world image can be mathematically modelled as follows:

$$y(n_1,n_2) = x_1(n_1,n_2)^* x_2(n_1,n_2) + \xi(n_1,n_2) \tag{8}$$

where $x_1(n_1,n_2)$ is an original scene, $x_2(n_1,n_2)$ is impulse response of the blur function, $\xi(n_1,n_2)$ is additive noise, $y(n_1,n_2)$ is the observed image and (*) is the two dimensional convolution operator. Additive noise statistics (such as variances etc..) introduced by imaging or electronic system are assumed to be known. This type of noise can then be easily removed from the image by using basic algorithms (Wiener filtering etc..). Additive noise introduced by imaging or electronic systems is not considered within the context of this work. Therefore, the resulting observation which is our degraded image model can be written as,

$$y(n_1,n_2) = x_1(n_1,n_2)^* x_2(n_1,n_2) \tag{9}$$

As seen, blur is a convolution problem between the original scene and the blur function[1,2]. In case of the real world image, atmospheric turbulence corrupts the image as modelled in Equation (9). Here, the blur function $x_2(n_1,n_2)$ can have different distributions and each distribution brings some new degradation process. This fact makes the problem very complex. But, considering the most general condition, the blur function based on unfocused optical imaging systems, atmospheric turbulence etc... have a normal or Gaussian distribution which comprises most of the other distributions. A gaussian distribution can be written as,

$$f(n_1,n_2) = \frac{1}{2\pi\sigma^2} e^{-\frac{(n_1^2+n_2^2)}{2\sigma^2}} \tag{10}$$

The real world images have been blurred by the Gaussian effect given in equation (10) which has been used to establish our restoration filter model. But, the real time imaging has a different problem, because of the atmospheric turbulence which is variable with time and space. These variations causing nonlinearity in restoration affect the restoration filter performance and filter coefficients can stay out of order during the restoration process. To overcome the non-linearity problem, blur function model parameters are continuously estimated from the degraded image. As long as the coefficients of blur function could properly be estimated from the degraded image, a good approximation of original scene would be obtained.

Now, a filter can be constructed by using the model given in Equation (10)[17,18]. But, there is still a complication in designing of the new filter in real time, because the variance, the mean and the kernel size of blur function affect the filter performance. Therefore, the restoration algorithm needs large computation times and numerous iterations for convergence. To simplify the problem, the blur kernel size has been chosen as a fixed value with a zero mean. Although this process decreases the iteration number from 125 to 15 [17], the performance quality of the restored image can not considerably affected.

The filtering process has been handled in the cepstral domain [5,10,13], because convolution is a complex procedure in the spatial domain. Fourier domain Cepstral transformation of Equation (9) is,

$$\hat{Y}(\omega_1, \omega_2) = \hat{X}_1(\omega_1, \omega_2) + \hat{X}_2(\omega_1, \omega_2) \quad (11)$$

We may express the filtering in the Cepstral domain as follows:

$$\hat{Y}_f(\omega_1, \omega_2) = \hat{X}_1(\omega_1, \omega_2) + \hat{X}_2(\omega_1, \omega_2) - \hat{F}(\omega_1, \omega_2) \quad (12)$$

where $\hat{Y}_f, \hat{X}_1, \hat{X}_2$ and $\hat{F}$ are the restored image, original scene, blur function and filter respectively.

3. ON-LINE ADAPTIVE FILTER CONTROLLER STRATEGY

The restoration problem is expressed in a block diagram of an on-line adaptive filter controller algorithm given in Figure-1, where, x and y_f are the input and the output of the restoration system, y is the output signal obtained from the observation model, b and b' are suitable coefficients for scenery and observed images, ε is a difference error between the unmeasured random noise (ξ) and the real characteristic convergency error obtained from the computation of the filter prediction. Here, the error function *f*(ε) is an even function and it can be expressed as

$$f(\varepsilon) = \varepsilon^2 \quad (13)$$

Since, the filter controller depends on x ,b', and ξ, an optimization approach is necessary in order to evaluate the model coefficients b' such that,

$$S = M\{f(\varepsilon)\} = M\{f[y_f(x,\xi,b') - y(x,b)]^2\} \quad \rightarrow \quad \min_b \quad (14)$$

where, M is the mean operator and, S is total error to be minimized. Here, the model parameters have been obtained via the real time adaptive filter controller algorithm with iteration steps as follows:

$$b^{i+1} = b^i + \Delta b^i[y(i+1);\ x(i+1)] \quad (15)$$

where, b^{i+1} is the parameter vector of the model coefficients in time duration $(i+1)$, Δb^i are corrections based on measurements at iteration i.

Error measurements have been realized by using the mean square error criteria as follows,

$$E = \sum_{n_1=1}^{N}\sum_{n_2=1}^{M}\left(y_f(n_1,n_2) - y(n_1,n_2)\right)^2 \quad (16)$$

where E is the energy of error signal between input y (degraded image) and output y_f (filtered output). N and M are chosen as 200x200 image size in this work Energy (E_1) of input signal is,

$$E_1 = \sum_{n_1=1}^{N} \sum_{n_2=1}^{M} \left(y(n_1, n_2) \right)^2 \qquad (17)$$

According to Equations (18) and (19), improvement in image quality in dB units is obtained as

$$\text{Im}\,provement = 10\log_{10} \frac{E_1}{E} \qquad (18)$$

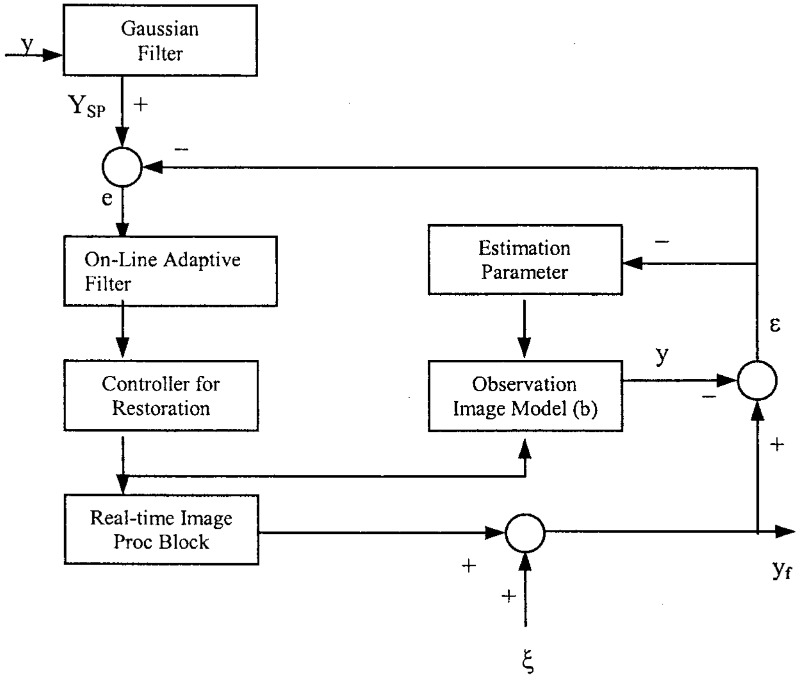

Figure-1. On-line model Adaptation for the algorithmic filter controller structure.

4. REALIZATION ALGORITHM

In this work, an on-line adaptive filter controller algorithm has been realized to solve the restoration problem in real time. The proposed algorithm can be explained shortly as follows:

1. Read digitized image ($y(n_1,n_2)$), (Equation 9)
2. Estimate the filter parameter i.e. variance (σ^2) using the edge map of degraded image following 15 iterations steps. This step takes 30 seconds on 466 MHz computer for an 200x200 pixel image. Estimation procedure of filter coefficients is performed in every 30 second. Restoration of images continues during this period.

3. Construct a restoration filter using the computed parameter in step 2 (filter model $f(n_1,n_2)$ as given in Equation 10),
4. Compute the Cepstral transformation of both filter f and image y,
5. Apply the designed filter to blurred image ($\hat{Y} - \hat{F}$), (Equation 12)
6. Compute the inverse Cepstral transformation of step-5. This step is the result of restoration for actual image.
7. Apply another blurred image for real time application and restore the new blurred image using steps 3,4,5,6
8. Reestimate the filter parameter continuously according to step-2 and compare it with the previous filter parameter. If the error remains under a critical value, go on to restoration, else, refresh the filter parameter using a new value and design a new filter using new parameter and go on restoration.

Here, the gradient edge algorithm [5,13] is used to estimate the blur parameter from the existing image information, where the restoration filter coefficients are periodically updated in a certain time duration. Parameter estimation and filter coefficient updating procedure is realized as follows;

1. Compute the edge map of degraded image,
2. Construct a restoration filter with edge information in step-1 and restore the image,
3. Compute the edge map of step-2,
4. If there is an enhancement in edge map, save this result and go on for new enhancement,

Else, go on iteration from step-1 with updated filter coefficients,

If there is no enhancement in consecutive five or more iteration steps, finish the iteration.

In fact, estimation and updating procedure of filter coefficients runs continuously and gives a result in every 30 secs for 200x200 pixels image. This result is compared with previously estimated coefficients mentioned as mentioned above. If the error exceeds a critical band , then restoration filter coefficients are updated and algorithm runs for restoration with new filter coefficients. Filter coefficients estimation process is realized by using the edge map of the degraded image. This process is based on an edge enhancement procedure on existing image. The best edge map obtained in the iterations steps is related on filter parameter in Gaussian model. In other words, information obtained from the model estimation and the real world images are continuously compared. If there is a difference in between, then the filter coefficients are updated. Here, if the difference error ε_y does not exceed the critical error ε_0 ($\varepsilon_y < \varepsilon_0$), then the restoration can be realized by using the previous information. Vice versa, model parameters must be updated in order to increase the restoration quality and to hold the performance characteristics in a given range for the model adaptation.

Table-1. Restoration results for the presented method

Images	Real Variance	Estimated Variance	Blur Kernel	MSE in Blurred Image	MSE in Restore d Image	Improvement in Image Quality in (dB)
Fig-2	4	3.960	5	280.69	2.79	36.87
Fig-2	6	5.930	5	270.77	5.29	34.07
Fig-2	9	8.983	5	269.93	0.77	42.43
Fig-2	4	4.100	15	859.11	23.93	27.53
Fig-2	6	6.003	15	830.48	0.013	48.49
Fig-2	9	8.946	15	810.2	3.70	35.63
Fig-3	4	3.992	5	45,57	0.033	44.87
Fig-3	6	6.009	5	43.99	0.062	38.21
Fig-3	9	9.006	5	43.85	0.031	45.12
Fig-3	4	3.998	15	138.30	0.002	65.70
Fig-3	6	6.018	15	130.74	0.84	30.85
Fig-3	9	8.987	15	125.34	0.30	35.30
Fig-4	4	3.996	5	551.52	0.324	43.67
Fig-5	4	3.997	5	1055.8	0.177	49.94
Fig-6	Unknown	4.206	15	------	----	8.55
Fig-7	Unknown	2.011	15	------	----	9.06

5. RESULTS AND DISCUSSION

In this section, we present the results of applying the restoration algorithm to 200x200 simulated and real world images. To start with, photographic images were artificially blurred by a gaussian distribution under the different blur coefficients. Here, the algorithm estimates the blur model parameters to build a restoration filter and then restores it. Table-1. shows the numerical results with the blur kernel size 5 and 15. The images of Figure-2 and Figure-3 in Table-1 have been consecutively applied to the algorithm after they have been degraded by the variances 4, 6 and 9 (for the blur kernel 5 and 15).

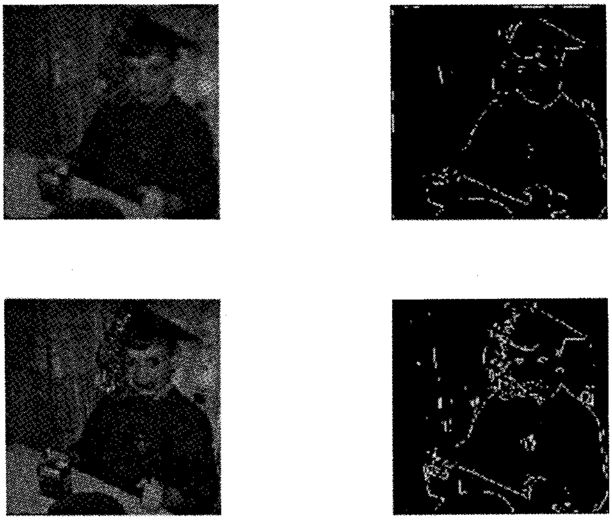

Figure-2. a.) Synthetically blurred image with variance 4 (left above), b.) Edge map of (a) (right above), c.) Restored image from (a) (left below), d.) Edge map of (c) (Right below)

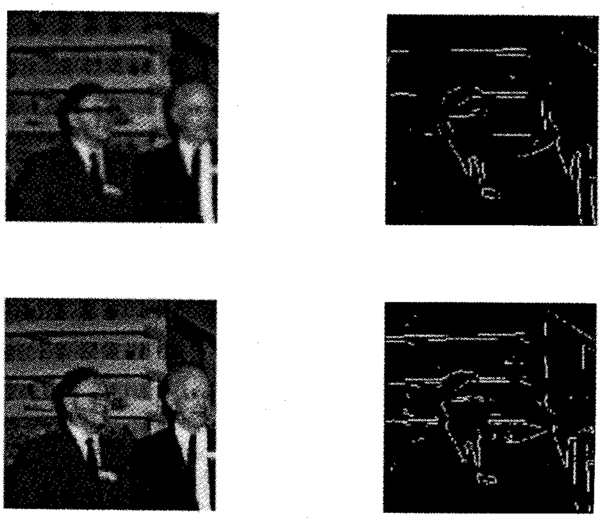

Figure-3. a.) Synthetically blurred image with variance 4 (left above), b.) Edge map of (a)(right above) , c.) Restored image from (a). Note that, the same filter parameter in Figure-2. has been used for restoration (left below), d.) Edge map of (c) (Right below)

Estimation results, improvement in image quality and MSE (Mean Square Error) are considerable as shown in Table-1. Note that, differences between Figure-2.c and 2.a, Figure 3.c and 3.a or Figure 4.b and 4.a and Figure 5.b and 5.a are clearly confirm the results. We did not use the critical error parameter in computations of Table-1 to show the correctness of estimation results of the algorithm. In this case, changes in restoration results are rather small. But in real-time applications, critical error criteria have been used to shorten the computation time.

Figure-4. a.) Synthetically blurred Lena image with variance 4 (left above), b.) Restored image from (a) using the new estimated filter

Figure-5. a.) Synthetically blurred cameraman image with variance 4 (left above), b.) Restored image from (a) using the new estimated filter

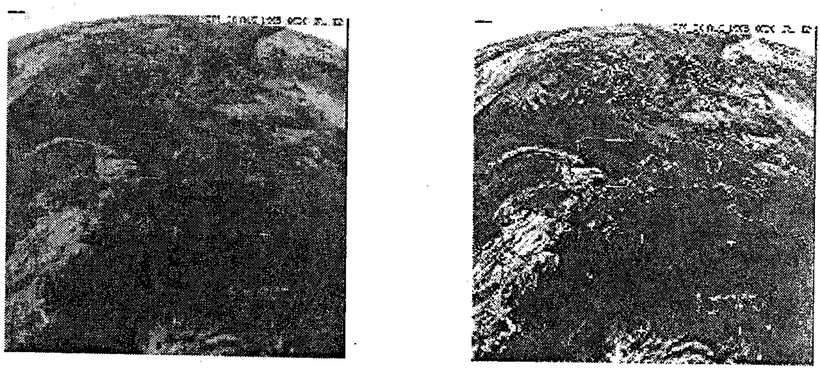

Figure-6. a.) An original blurred satellite image taken by Meteostat (Left)
b.) Restored image from (a) (Right)

Figure-6. and 7. show the real world images that have been taken by satellite from different places. Here, each image is blurred differently by changing atmospheric conditions. The algorithm begins to adapt the blur parameter of the image shown in Figure-6.a and then restores it estimating the variance as 4.206 with 8.55 dB improvement (Figure-6.b). Then, the algorithm is applied to the other real world images shown in Figure 7.a. Here, a discrepancy error is observed between the previous and the actual blur parameters, so, the algorithm estimates the blur parameter of the new image as 2.011. Figure-6.b and 7.b show restored real world images respectively.

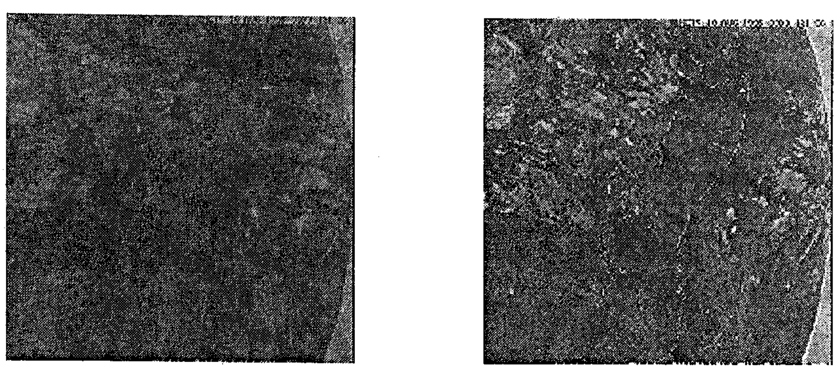

Figure-7. a.) An original blurred image taken by HST (left)
b.) Restored image from (a) (right) ,

Simulated images in Table-1 (Figure-2,3,4,5) are only corrupted by the effect of blurring. Therefore, the restoration errors (MSE) are very low and improvements in image quality in dB are considerable. But, in the real world images, there are some unmeasurable and uncontrollable observation noises superimposed on the image. The origin of the mentioned noises seems not to be very clear. Our filter model partially compensates these effects, but not entirely. Therefore, the improvements in image quality on real world images (Figure-6 and 7) are not as good as simulated images.

Table-2. is given to compare our results with some previously published results. In generalized cross validation [14] (GCV) method, variance is estimated with an error of 0.03 and MSE is 198.4 as shown in Table-2. Also, in Table-2, variance is estimated with an error of 0.08 and MSE is 159.67 when maximum likelihood [14] (ML) estimation is used. Our results yields further improvements in estimation and restoration with respect to above mentioned (in Table-2) results.

Table-2. Comparisons for variance estimation and MSE in restored images[8]

Methods	Real Variance	Estimated Variance	Blur Kernel	MSE
GCV	4	4.03	5	198.4
ML	4	4.068	5	159,67

In our method, If the atmospheric conditions or the other environmental factors change with time and place, the algorithm senses the new condition and updates the filter model parameter for a reliable restoration. Note that, atmospheric conditions do not change as fast as new parameter estimates so the algorithm will have enough time to estimate the blur function model parameter. If the computer would have a parallel structure or faster microprocessors, then all process times could more considerably be decreased for real time applications.

6. CONCLUSION

In this study, a new real time algorithm has been proposed to restore the blurred images consecutively. If the incompatibility error between the existing information and the output information of model estimation exceeds the critical error, then the adaptation (estimation of filter parameter) of filter model to a new image is required. In this condition, the filter model parameter must be updated with the estimated new one. If this can not be made, the image quality could not be as well as desired.

Algorithm has only fifteen iteration steps for estimation of the filter coefficients. It can be used for real time image restoration successfully, as it performs in a short computation and restoration time.

Another advantage of the algorithm is the improvement in image quality as shown in the figures and Table-1. Also, some experimental results with simulated images are given in Table-2 to compare our results with the previously published algorithms.

The real time adaptive filter controller algorithm developed for a clear identification of the remote sensing images does not effected from the change of the contrast and the position angle of the scenery.

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