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INVESTIGATION OF RESTORATION TECHIQUES FOR REMOTE SENSING SATELLITE IMAGERY

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Abstract:

This paper introduces implementation of some image restoration techniques, which can be applied for satellite images. These techniques are, inverse filter, iterative method, wiener filter, regularized deconvolution filter and wavelet-based method. The restoration techniques are applied on several satellite images associated with atmospheric turbulence blur at different variance of additive noise to check the performance of each technique and its capability to restore the degraded image as close as possible to the original image. Also, comparison studies between these techniques are introduced based on measures like Peak Signal-to-Noise Ratio (PSNR) and Root Mean Square Error (RMSE). The experimental results show that: the wavelet method is the most suitable restoration technique for satellite images, since it gives high PSNR and small RMSE with respect to the other restoration techniques.

Keyword: Image restoration, Remote sensing, Image blur models.

1- Introduction

When image data is recorded by sensors on satellites and aircrafts. It may contain some degradations. The degradation comes in many forms such as motion blur, noise, atmospheric turbulence and camera misfocus. Thus when an image is to be utilized, it is necessary to make corrections. These corrections are achieved by image restoration, which is a process that attempts to recover an image that has been degraded by using some priori knowledge of the degradation phenomenon. Therefore restoration techniques are oriented toward modeling the degradation and applying the inverse process in order to recover the original image [1].

The image restoration techniques that are described in this paper in frequency domain and fall under the class of linear spatially invariant restoration filters. Assuming that the blurring function acts as a convolution kernel or point-spread function (PSF) that does not vary spatially. It is also assumed that the statistical properties (mean and correlation function) of the image and noise do not change spatially. Under these conditions the restoration process can be carried out by means of a linear filter of which the PSF is spatially invariant, i.e., is constant throughout the image [2].

This paper is organized as follows: *Section 2* presents the problem statement and the proposed solution of the image degradation / restoration process. *Section 3* introduces the atmospheric turbulence blur model. *Section 4* introduces a study analysis on some of restoration techniques. *Section 5* shows the analysis that is performed on the most popular restoration techniques, and the comparative study between these techniques. *Section 6* concludes the work results. Finally, references are given in section *7*.

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2- Problem statement

The general problem is the restoration (deconvolution) of a satellite image from blurred and noisy data. Fig. (1) shows, the degradation model, which is represented in the spatial domain by [1], [2]:

$$\boldsymbol{g(x, y) = d(x, y) \otimes\otimes f(x, y) + \eta(x, y)} \quad \textbf{(1)}$$

Where $f(x, y)$ and $g(x, y)$ denote respectively the original and observed degraded image, $d(x, y)$ is the impulse response of the degradation function, $\otimes\otimes$ two-dimensional (2-D) discrete linear convolution and $\eta(x, y)$ is the additive noise. Sometimes the noise is assumed to have a Gaussian probability density function with zero mean and to be white.

Fig. (1) shows the objective of restoration process is to obtain an estimate $f^{\wedge}(x, y)$ to be as close as possible to the original image $f(x, y)$ given $g(x, y)$ and $d(x, y)$. In general, the more known about d and η the closer $f^{\wedge}(x, y)$ will be to $f(x, y)$.

So the equivalent frequency domain of Eq. (1) is [1], [2]:

$$\boldsymbol{G(u, v) = D(u, v) * F(u, v) + N(u, v)} \quad \textbf{(2)}$$

Where (u,v) are the spatial frequency coordinates, and capitals represent Fourier transforms.

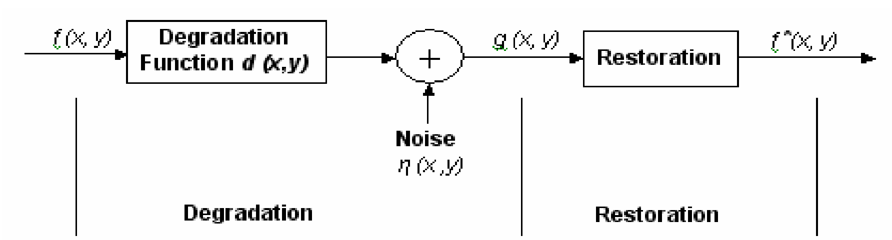


Fig. 1. A model of the image degradation / restoration process

3- Atmospheric Turbulence Blur Model

The PSF $d(x, y)$ describes how the imaging system distributes the radiation field received from a point source or point scatter and hence governs the resolution that can be obtained. The PSF also determines the frequency content of the image since high resolution is associated with high frequency information. The narrower the PSF, the greater the frequency content of the image and greater its resolution. The result of deconvolving (deblurring) an image is to increase its spatial frequency content and hence restore its resolution [3]. For spatially continuous blurs and for spatially discrete blurs the PSF is constrained to satisfy [2]:

$$\int_{-\infty}^{\infty}\int_{-\infty}^{\infty} d(x, y)\, dxdy = 1 \quad \textbf{(3)}$$

$$\sum_{n1=0}^{N-1}\sum_{n2=0}^{M-1} d(n_1, n_2) = 1 \quad \textbf{(4)}$$

The common type of PSF that affect the satellite images is the atmospheric turbulence, which 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, and exposure time), for long – term exposures the PSF can be described reasonably well by a Gaussian function. Here σ_G determines the amount of spread of the blur, and constant C is to be chosen so that Eq. (3) is satisfied [2].

$$d\left(x, y; \sigma_G\right) = C \exp\left(-\frac{x^2 + y^2}{2\sigma_G^2}\right) \tag{5}$$

4- Image Restoration Techniques

In this section the PSF of the blur is satisfactory known. The methods will be introduced for removing the blur from the recorded image using a linear filter are inverse filter, iterative method, wiener filter, regularized deconvolution filter and wavelet-based method.

4.1 Inverse Filter

The simplest approach to restoration is direct inverse filtering, where an estimate $F^{\wedge}(u, v)$, of the original image simply is computed by dividing the degraded image, $G(u, v)$, by the degradation function $D(u, v)$ in the absence of noise. The inverse filtering responds very badly to any noise in the image because noise tends to be high frequency [4].

$$F^{\wedge}(u, v) = \frac{G(u, v)}{D(u, v)} \tag{6}$$

Substituting the right side of Eq. (2) for $G(u\ v)$ in Eq. (6) yields

$$F^{\wedge}(u, v) = F(u, v) + \frac{N(u, v)}{D(u, v)} \tag{7}$$

In the ideal case, invert all the elements of **D** to get a high pass filter. However, notice that a lot of the elements in **D** have values either at zero or very close to it. Inverting these elements would give us either infinities or some extremely high values. In this case the ratio $N(u, v) / D(u, v)$ could easily dominate the estimate $F^{\wedge}(u, v)$. In order to avoid these values, **D** should be thresholding before taking the inverse, as follows [5]:

$$D(u, v) = \begin{cases} D(u, v) & \text{if} \quad D(u, v) > n \\ n & \text{otherwise} \end{cases} \tag{8}$$

Where n is a threshold, and set arbitrarily close to zero for noiseless cases, but in case of noise it higher than zero.

4.2 Iterative Method

The idea behind the iterative procedure is to make some initial guess of f based on g and to update that guess after every iterations. The basic form of iterative restoration filters is the one that iteratively approaches the solution of the inverse filter, and it is given by the following spatial domain iteration:

$$f_o^{\wedge}(n_1, n_2) = \lambda * g(n_1, n_2) \tag{9}$$

$$f_{k+1}^{\wedge}(n_1,n_2) = f_k^{\wedge}(n_1,n_2) + \lambda * \left(g(n_1,n_2) - f_k^{\wedge}(n_1,n_2) ** d(n_1,n_2)\right) \quad \textbf{(10)}$$

Where $f_o^{\wedge}$ is an initial guess usually in the first iteration is chosen to be identical to zero or identical to *g*. Here $f_k^{\wedge}$ is the restoration result after k iterations. If the number of iterations becomes very large, then $f_k^{\wedge}$ approaches the solution of inverse filter. If our $f_k^{\wedge}$ is a good guess, eventually $f_k^{\wedge}$ convolved with *d* will be close to *g*. When that happens the second term in the $f^{\wedge}_{k+1}$ equation will disappear and $f_k^{\wedge}$ and $f^{\wedge}_{k+1}$ will converge. λ is our convergence factor and it lets us determine how fast $f_k^{\wedge}$ and $f^{\wedge}_{k+1}$ converge [6], [7].

If we take both of the above equations to the frequency domain, we get

$$F_o^{\wedge}(u,v) = \lambda * G(u,v) \quad \textbf{(11)}$$

$$F_{k+1}^{\wedge}(u,v) = f_k^{\wedge}(u,v) + \lambda * \left(G(u,v) - F_k^{\wedge}(u,v) * D(u,v)\right) \quad \textbf{(12)}$$

The convergence occurs if the convergence parameter λ satisfies:

$$|1 - \lambda D(u,v)| < 1 \quad \textit{for all } (u,v) \quad \textbf{(13)}$$

Where *D (u, v)* is the 2D discrete Fourier transform *(DFT)* of *d (x, y)* and $|z|$ denotes the magnitude of a complex number z. Using the fact that $|D(u,v)| \le 1$, this condition simplifies to [8]:

$$0 < \lambda < 2 , \quad D(u,v) > 0 \quad \textbf{(14)}$$

4.3 Minimum Mean Square Error (Wiener) Filtering

Wiener deconvolution can be used effectively when the frequency characteristics of the original image and additive noise are known. The Wiener filtering executes an optimal tradeoff between inverse filtering and noise smoothing. It removes the additive noise and inverts the blurring simultaneously. In the absence of noise, the Wiener filter reduces to the ideal inverse filter. The Wiener filtering is optimal in terms of the mean square error. In other words, it minimizes the overall mean square error (MSE) between the ideal and restored image in the process of inverse filtering and noise smoothing [1].

$$MSE = \mathrm{E}\left(f(n_1,n_2) - f^{\wedge}(n_1,n_2)\right)^2 \quad \textbf{(15)}$$

Where E {.} is the expected value of the argument. The Wiener filter in Fourier domain can be expressed as follows [1], [9]:

$$W(u,v) = \frac{D^*(u,v)}{|D(u,v)|^2 + \dfrac{S_{\eta\eta}(u,v)}{S_{xx}(u,v)}} \quad \textbf{(16)}$$

Where $S_{xx}(u,v) = |F(u,v)|^2$, $S_{\eta\eta}(u,v) = |N(u,v)|^2$ are respectively power spectrum of the original image and power spectrum of additive noise, *D (u, v)* is blurring filter and $D^*(u,v)$ is a complex conjugate of *D (u, v)*. It is easy to see that the wiener filter has two separate parts, an inverse filtering part and a noise smoothing part. It doesn't only perform the deconvolution by inverse filtering (high-pass filtering) but also removes the noise with a compression operation (low-pass filtering). When dealing with spectrally white noise, the spectrum $|N(u,v)|^2$ is a constant, which simplifies things considerably. However, the power spectrum of the undegraded image seldom is known.

An approach used frequently when these quantities are not known or cannot be estimated is to approximate Eq. (16) by the expression [1], [2]:

$$W(u,v) = \frac{D^*(u,v)}{|D(u,v)|^2 + \frac{1}{(SNR)^2}} \tag{17}$$

Where SNR is a constant represents a Signal-to-Noise ratio. The estimated image can be obtained by:

$$F^{\wedge}(u,v) = W(u,v)\, G(u,v) \tag{18}$$

4.4 Constrained Least Squares Filtering (Regularized filter)

Regularized filter is another approach for overcoming some of the difficulties of the inverse filter (excessive noise amplification) and of the Wiener filter (estimation of the power spectrum of the original image). A regularized filter requires Knowledge of only the mean and variance of the noise. These parameters usually can be calculated from a given degraded image, so this is an important advantage than the Wiener filter. A more reasonable expectation for the restored image is that it satisfies [1], [3], [9]:

$$\sum_{n_1=0}^{N-1}\sum_{n_1=0}^{M-1}\left(g(n_1,n_2) - d(n_1,n_2) ** f^{\wedge}(n_1,n_2)\right)^2 \approx \sigma_\eta^2 \tag{19}$$

Where σ_η^2 is noise variance. The regularized filter in Fourier domain can be expressed as follows:

$$H_{cls}(u,v) = \frac{D^*(u,v)}{|D(u,v)|^2 + \gamma\,|P(u,v)|^2} \tag{20}$$

Here γ is a tuning or regularization parameter that should be chosen such that Eq. (19) is satisfied, and $P(u,v)$ is the Fourier transform of the PSF of a 2-D high-pass filter .We recognize this function as a 2-D Laplacian operator as follows [1], [10]:

$$p(x,y) = \begin{bmatrix} 0 & -1 & 0 \\ -1 & 4 & -1 \\ 0 & -1 & 0 \end{bmatrix} \tag{21}$$

The estimated image can be obtained by:

$$F^{\wedge}(u,v) = H_{cls}(u,v)\, G(u,v) \tag{22}$$

4.5 Wavelet-Based Method

The Wiener filtering is the optimal tradeoff of inverse filtering and noise smoothing but in the case when the blurring filter is singular, the Wiener filtering actually amplifies the noise. Thus a denoising step is needed to remove the amplified noise. Wavelet method is a successful approach introduced recently by R. Neelamani et al. The idea of wavelet-based deconvolution technique for ill-conditioned systems is to employ both Fourier-domain Wiener-like and wavelet-domain regularization. The regularized inverse filter is introduced by modifying the wiener filter with a new-introduced parameter [11], [12]:

$$G_\alpha(u,v) = \frac{D^*(u,v)\,S_{xx}(u,v)}{|D(u,v)|^2 S_{xx}(u,v) + \alpha S_{\eta\eta}(u,v)} \tag{23}$$

The parameter (α = 0.27) can be optimally selected to minimize the overall mean-square error. The block diagram of the Wavelet restoration algorithm is displayed in Fig. (2) [13].

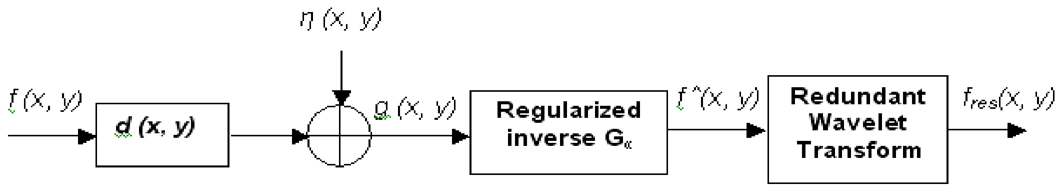


Fig. 2. The block diagram of the Wavelet restoration algorithm

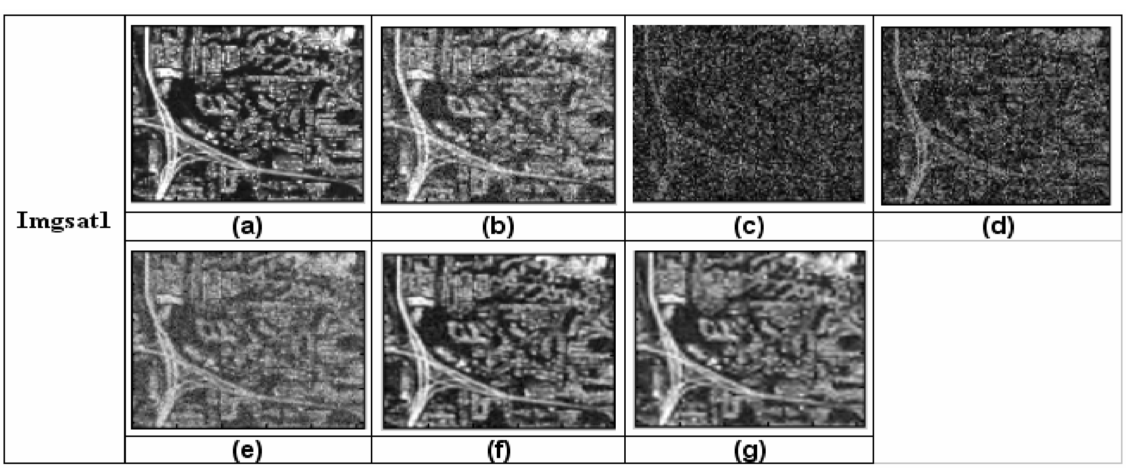
The operation start by applying the regularized inverse filter in Fourier domain to cancel the blurring in the noisy degraded image *g* to obtain $f^{\wedge}$. Apply the wavelet denosing algorithm in wavelet domain to reduce (smooth) the noise in $f^{\wedge}$ to obtain the restored image f_{res} .

5- Experimental work

The analysis is performed on inverse filter, iterative method, wiener filter, regularized deconvolution filter and wavelet-based method as the most popular restoration techniques. The comparative study between these techniques is applied on several satellite images with atmospheric turbulence blur at three different noise level using PSNR and RMSE as a metric measures.

To compare between these algorithms a set of 10 satellite sub-images are used namely *imgsat 1, imgsat 2,….imgsat 10* respectively. The images are acquired by the commercial Remote Sensing satellites SPOT 5 *(imgsat 1, imgsat 3, imgsat 5, imgsat 7, imgsat 9*) and LANDSAT 7 *(imgsat 2, imgsat 4, imgsat 6, imgsat 8, imgsat 10*). The images format is TIF, gray scale of 8-bit, and the images size is 256X256 pixels. The analysis programs are performed using MATLAB 6.5 with a PC whose configuration is (Pentium IV, Intel 2.6 GHz processor, 512 Mbytes cash memory, 256 Mbytes RAM).

To study the effect of the implemented restoration techniques on images with atmospheric turbulence blur at three different noise variance. Fig. (3) depicts an example of two original satellite images as shown in Fig. (3.a). Fig. (3.b) shows the noisy degraded image with atmospheric turbulence (σ_G = 1.2) and noise variance = 0.01. The results of applying the inverse filter, iterative method, wiener filter, regularized filter and wavelet-based method are shown in Fig. (3.c), Fig. (3.d), Fig. (3.e), Fig. (3.f), and Fig. (3.g) respectively.



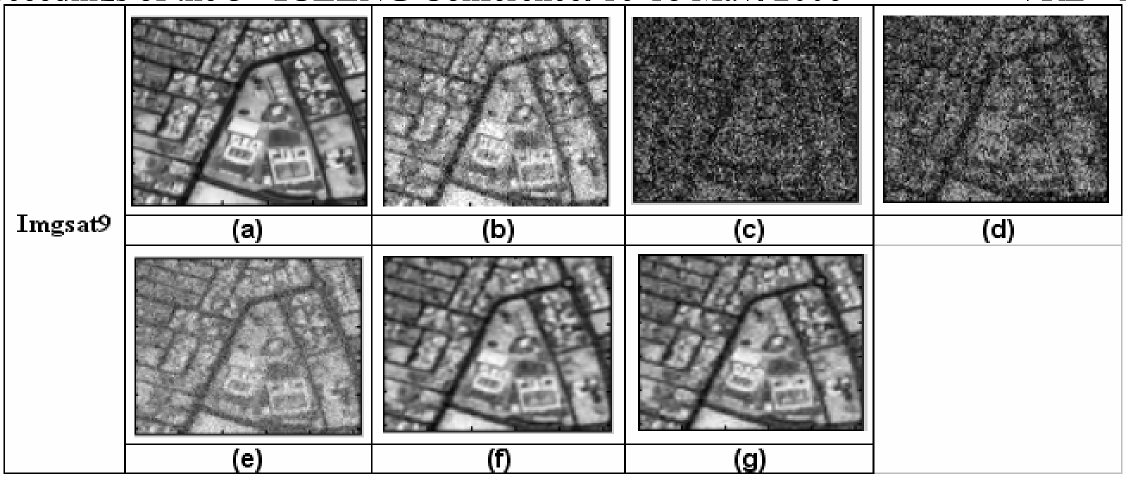


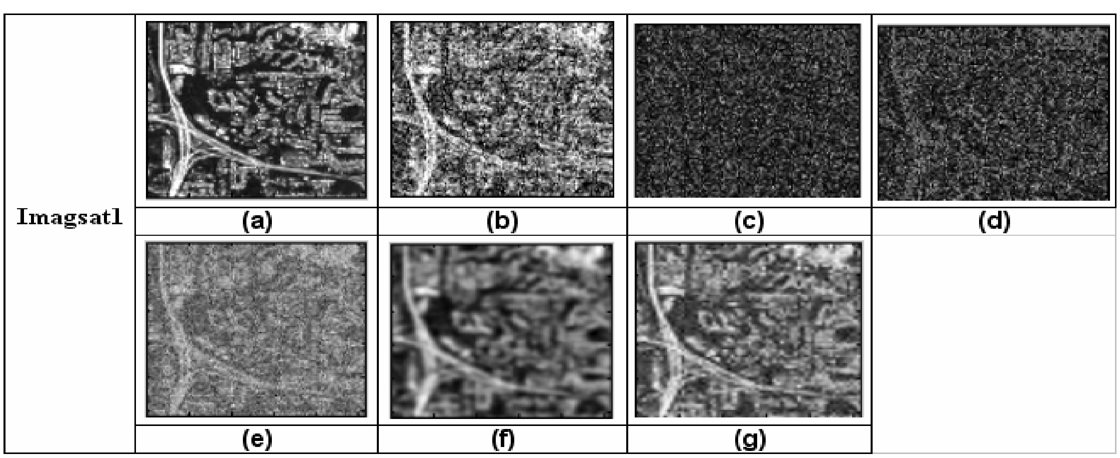
Fig. 3. An example of two satellite images after applying the different image restoration techniques with atmospheric turbulence ($\sigma_G = 1.2$) and noise variance = 0.01.

To evaluate the performance of the implemented restoration techniques and their capabilities to restore the degraded image as close as possible to the original image. The RMSE and PSNR are computed for 10 satellite sub-images at noise variance = 0.01, as reported in Table 1. From Table 1, it could be noticed that the wavelet-based method gives high average of PSNR and small average of RMSE with respect to the other restoration techniques.

Table 1. **Comparison of the different image restoration techniques with atmospheric turbulence ($\sigma_G = 1.2$) and noise variance = 0.01.**

Sat No	Inverse Filter		Iterative Method		Wiener Filter		Regularized Filter		Wavelet Method	
	PSNR	RMSE	PSNR	RMSE	PSNR	RMSE	PSNR	RMSE	PSNR	RMSE
Imgsat 1	8.853	92.018	12.102	63.305	18.773	29.327	21.052	22.589	18.747	29.454
Imgsat 2	8.569	95.072	11.824	65.357	19.750	26.242	26.580	11.954	26.326	12.308
Imgsat 3	8.350	97.507	11.303	69.397	17.028	35.902	18.319	30.943	18.220	31.296
Imgsat 4	8.720	93.439	12.145	62.987	20.000	25.499	29.787	8.2632	29.800	8.2510
Imgsat 5	10.02	80.431	13.795	52.093	20.824	23.191	22.262	19.653	25.157	14.082
Imgsat 6	9.157	88.849	12.667	59.314	19.757	26.222	26.584	11.948	26.583	11.950
Imgsat 7	9.738	83.103	13.560	53.522	20.389	24.382	26.081	12.660	28.769	9.2913
Imgsat 8	9.446	85.939	12.771	58.609	19.161	28.085	19.050	28.445	20.141	25.087
Imgsat 9	8.625	94.466	12.069	63.541	19.899	25.796	26.248	12.420	25.259	13.917
Imgsat 10	8.892	91.606	12.441	60.876	19.857	25.923	24.438	15.297	24.595	15.023
Average	9.037	90.243	12.467	60.900	19.543	27.056	24.040	17.417	24.359	17.065

To study the effect of increasing the noise variance on images. Fig. (4) depicts an example of two original satellite images as shown in Fig. (4.a). Fig. (4.b) shows the noisy degraded image with atmospheric turbulence ($\sigma_G = 1.2$) and noise variance = 0.05. The results of applying the inverse filter, iterative method, wiener filter, regularized filter and wavelet method are shown in Fig. (4.c), Fig. (4.d), Fig. (4.e), Fig. (4.f), and Fig. (4.g) respectively.



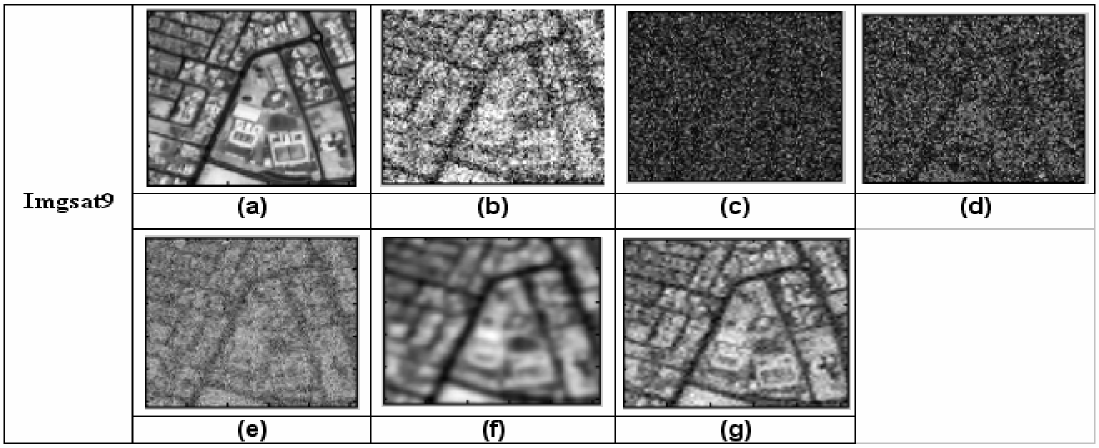


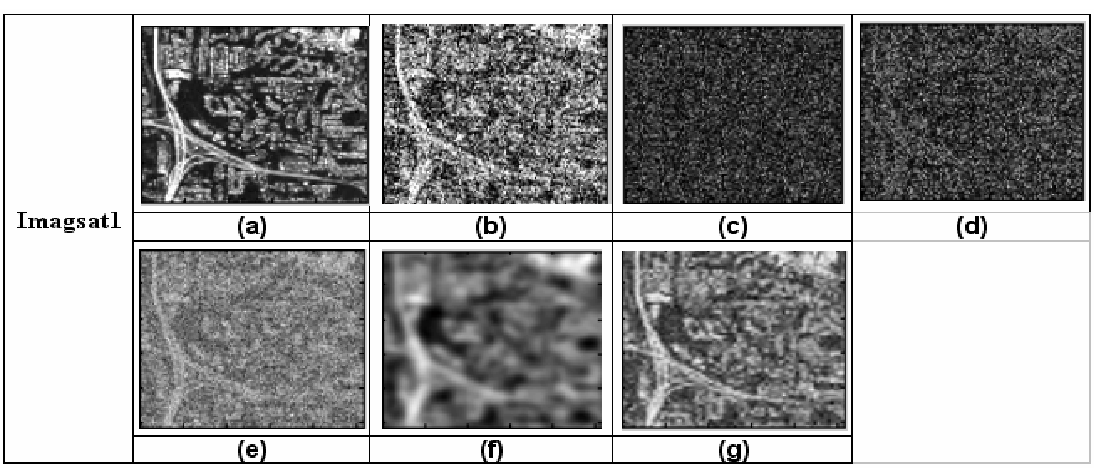
Fig. 4. An example of two satellite images after applying the different image restoration techniques with atmospheric turbulence ($\sigma_G = 1.2$) and noise variance = 0.05.

Again, The RMSE and PSNR are computed for the same 10 satellite sub-images at noise variance =0.05, as reported in Table 2. From Table 2, it could be noticed that the wavelet-based method gives high average of PSNR and small average of RMSE with respect to the other restoration techniques.

Table 2. Comparison of the different image restoration techniques with atmospheric turbulence ($\sigma_G = 1.2$) and noise variance = 0.05.

Sat No	Inverse Filter		Iterative Method		Wiener Filter		Regularized Filter		Wavelet Method	
	PSNR	RMSE	PSNR	RMSE	PSNR	RMSE	PSNR	RMSE	PSNR	RMSE
Imgsat 1	2.878	183.063	7.167	111.735	13.337	54.913	16.764	37.008	17.884	32.534
Imgsat 2	2.806	184.599	6.989	114.037	13.244	55.501	22.991	18.070	23.194	17.652
Imgsat 3	2.921	182.165	6.888	115.378	12.759	58.688	16.328	38.914	17.546	33.824
Imgsat 4	2.808	184.554	7.094	112.670	13.397	54.536	22.780	18.515	24.736	14.780
Imgsat 5	3.613	168.207	7.971	101.847	14.533	47.851	14.737	46.736	21.202	22.203
Imgsat 6	2.835	183.976	7.353	109.361	13.522	53.756	20.340	24.518	23.414	17.211
Imgsat 7	3.101	178.431	7.743	104.559	14.031	50.694	17.112	35.555	23.596	16.854
Imgsat 8	4.445	152.855	8.069	100.711	14.586	47.554	13.281	55.270	18.276	31.098
Imgsat 9	2.984	180.854	7.187	111.478	13.539	53.649	19.895	25.809	22.642	18.811
Imgsat 10	3.114	178.168	7.320	109.781	13.757	52.319	18.068	31.852	22.069	20.093
Average	3.150	177.690	7.378	109.160	13.670	49.089	18.229	33.224	21.455	22.506

Fig. (5) depicts an example of two original satellite images as shown in Fig. (5.a). Fig. (5.b) shows the noisy degraded image with atmospheric turbulence ($\sigma_G = 1.2$) and noise variance = 0.1. The results of applying the inverse filter, iterative method, wiener filter, regularized filter and wavelet-based method are shown in Fig. (5.c), Fig. (5.d), Fig. (5.e), Fig. (5.f), and Fig. (5.g) respectively.



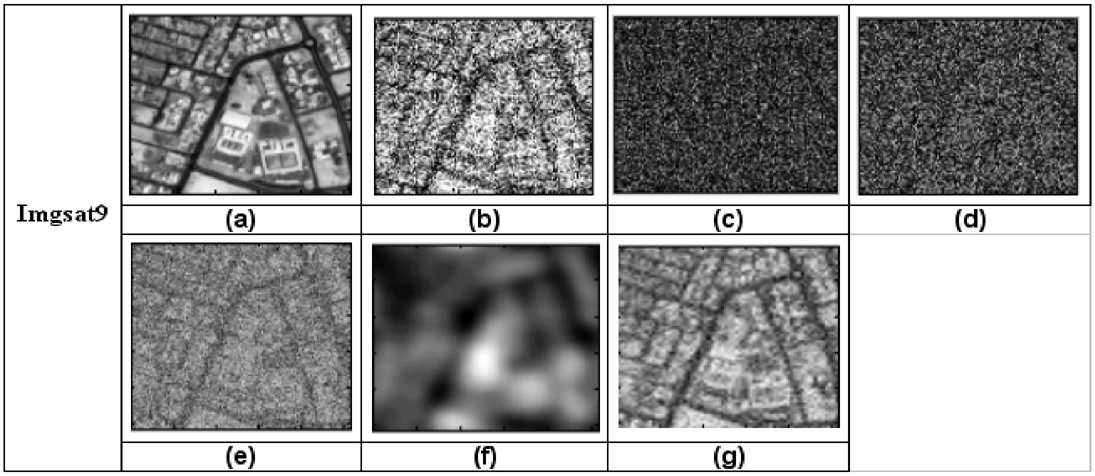


Fig. 5. An example of two satellite images after applying the different image restoration techniques with atmospheric turbulence ($\sigma_G = 1.2$) and noise variance = 0.1.

Again, The RMSE and PSNR are computed for the same 10 satellite sub-images at noise variance = 0.1, as reported in Table 3. From Table 3, it could be noticed that the wavelet method gives high average of PSNR and small average of RMSE with respect to the other restoration techniques.

Table 3. Comparison of the different image restoration techniques with atmospheric turbulence ($\sigma_G = 1.2$) and noise variance = 0.1.

Sat No	Inverse Filter		Iterative Method		Wiener Filter		Regularized Filter		Wavelet Method	
	PSNR	RMSE	PSNR	RMSE	PSNR	RMSE	PSNR	RMSE	PSNR	RMSE
Imgsat 1	0.492	240.945	5.145	141.722	11.117	70.901	13.460	54.141	17.204	35.180
Imgsat 2	0.425	242.809	5.153	140.882	10.978	72.044	21.452	21.574	21.678	21.020
Imgsat 3	0.637	236.958	5.170	140.609	10.847	73.145	12.563	60.031	16.855	36.624
Imgsat 4	0.365	244.487	5.088	141.948	11.090	71.120	18.608	29.930	22.350	19.454
Imgsat 5	0.943	228.765	5.487	135.571	12.066	63.564	12.383	61.286	18.820	29.209
Imgsat 6	0.326	245.594	5.075	142.155	11.242	69.893	16.152	39.710	21.615	21.172
Imgsat 7	0.527	239.984	5.199	140.135	11.714	66.194	16.740	37.114	20.860	23.095
Imgsat 8	2.194	198.063	6.165	125.390	12.103	63.297	9.442	85.988	16.657	37.469
Imgsat 9	0.631	237.109	5.289	138.701	11.257	69.772	14.804	46.377	20.999	22.728
Imgsat 10	0.661	236.312	5.284	138.778	11.434	68.365	12.898	57.759	20.253	24.765
Average	0.720	235.100	5.305	138.590	11.384	68.829	14.850	49.391	19.729	27.071

Fig. (6) depicts the effect of three different noise levels with atmospheric turbulence blur after applying the wavelet restoration technique.

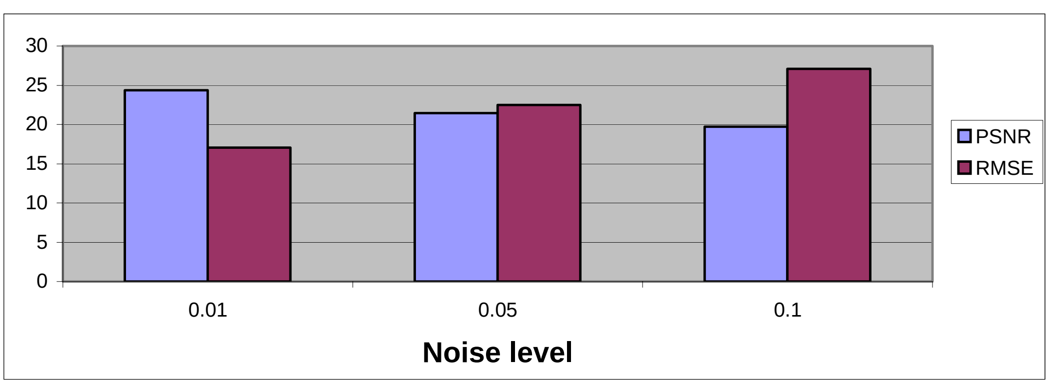


Fig. 6. The effect of increasing the noise levels with atmospheric turbulence blur after applying the wavelet restoration technique.

6- Conclusion

The experimental results showed that,

- The inverse filtering and iterative method do not deal well with noise but the iterative method deals a little better with noise than the inverse filtering. Also, the regularized filter requires Knowledge of only the mean and variance of the noise. These parameters usually can be calculated from a given degraded image, so this is an important advantage than the wiener filter. Finally the wavelet-based method is the most suitable restoration technique for satellite images, since it gives high PSNR and small RMSE with respect to the other restoration techniques.

- Increasing the noise level leads to increasing the RMSE and decreasing the PSNR

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