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Haze Reduction from Image by Adaptive Inverse Filter and Haar Wavelet Transform

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Abstract: *In this paper we have designed an inverse filter based on Wiener filter to remove haze fromimage. We have used Steering Kernel Regression and also Wavelet Transform to enhance the restored image. Our proposed algorithm has been applied on Wild database. Results showed that improving inverse filter by Wavelet Transform has better quality.*

Keywords: *Inverse filter, Steering Kernel Regression, Wiener filter, Wavelet transform.*

I. Introduction

Noise reduction is a prominent and vital procedure in image processing. In [1] particles in the space are divided to: haze, fog, cloud, rain and snow. The direction of scattered incidents from a particle in the atmosphere is directly related to the particle's size. How much the size increases, the direction of scattered incidents tends to be radiated to forward. As in the size of equal to the incidenceswavelength, it was assumed that the particle has a role like a point source, scattering almost all of the beams to forward direction. In mechanisms of atmospheric scattering, attenuation of incidence and effect of airlightwere discussed [1, 2]. Other important subject in vision in the bad weatheris how to make a good estimation of the distances between objects to the observer. But as mentioned in[3], estimation of the distances makes the algorithm tobe dependent to the prior knowledge about physical conditions of particles in the atmosphere. This reason persuaded usto find a new way to increase our vision in the bad weather without any need of estimation of objects. Wiener filter [4] is an adaptive filter that we have chosen for a restoration process.

In restoration process, first we find a way to make the degradation model of an image. This helps us to derive a kind of inverse process to restore the image. Enhancement is other process to increase the quality of an image,used when information is still in image pixels, but it is not clear [5]. For enhancement we have used two methods of Haar Wavelet transform [6] and Steering Kernel Regression [7].

II. Restoration

Wiener filter uses minimum mean square error to make an estimation of desired signal. In spatial domain Wiener filter calculates the ratio of correlation between desired signal and degraded signal to autocorrelation of desired one [8]. In frequency domain we can write the Wiener filter impulse response as (1) [9].

$$\mathbf{\Phi}(f) = \frac{|S(f)|^2}{|S(f)|^2 + |N(f)|^2} \tag{1}$$

Where S(f) is a part of signal that is not corrupted with noise. N(f) is signal of noise In (2), c(n) is an input signal, n(n) is the additive noise and s(n) is the desired signal.

$$c(n) = s(n) + n(n) \tag{2}$$

When we use Wiener filter, it is assumed that the noise distribution is normal and noise is additive [10]. We have chosen two images from WILD database [11], asdesired and noisy images. Theimages areused as reference images in Wiener filter. An inverse process, based on degradation's informationobtained from Wiener filter is used to restore the input image [5].

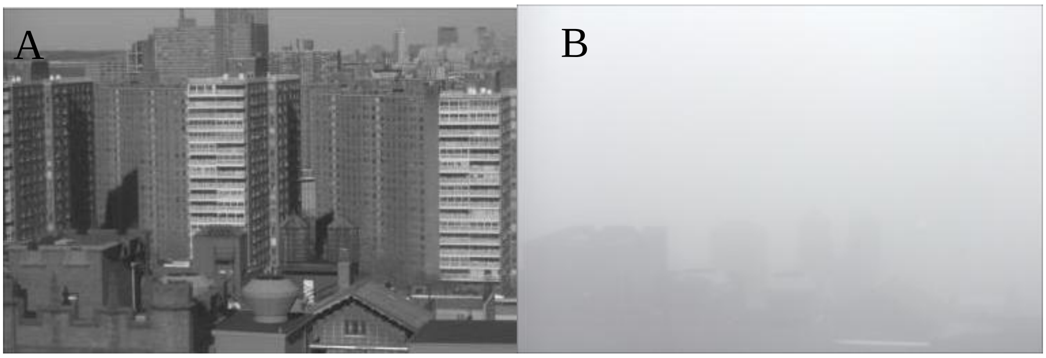

Figure (1): the reference images from WILD database, (A): Original image, (B): Observed image.

Figure (2), illustrates how an inverse filter work. In figure (2), G(z) is an unknown system, H(z) is an inverse filter, Z^{-D} is a delay block, v(n) is additive noise, x(n) is input signal, y(n) is desired signal and e(n) is error between output and desired signal [12].

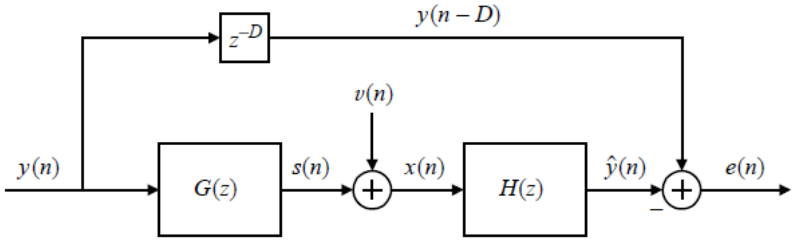

Figure (2) : block diagram of an inverse filter.[12].

Key point in our inverse filter is to find a way to remove the effect of zeros in Wiener filter. We replaced zeros with a parameter and named it γ.

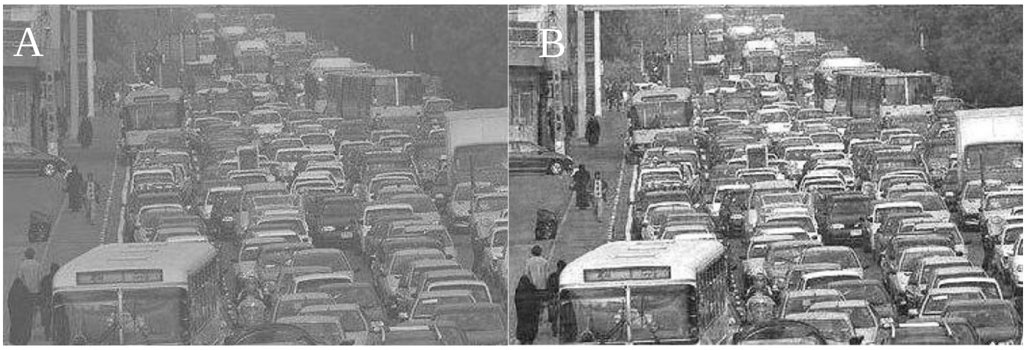

Figure (3): results of our proposed inverse filter. A: input image from [13], B: output image of our proposed inverse filter.

Figure (3) and figure (4), are not belong to WILD database but they are provided from other sources [13, 14] for an extra effort. In both figures (3 & 4) there is not any further enhancement. As it is shown in the following section, an extra enhancement method applied to improve the quality of images (see figures (7 & 8)). In figure (3) the scalar R is equal to 1 and value of γ is 1.8, but infigure (4), we put the value of R equal to 0.9 and γ to 2.8, because there is more density of haze particles in figure (4).

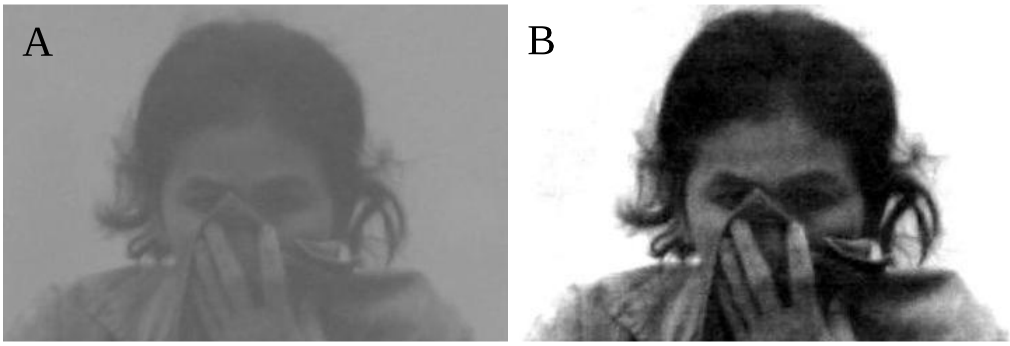

Figure (4): results of our proposed inverse filter. A: input image from [14], B: output image of our proposed inverse filter.

III. Enhancement

In this section we have tried to improve the quality of output images. Steering Kernel Regression (ISKR) and Haar Wavelet Transform are two methods that we have used to enhance images.

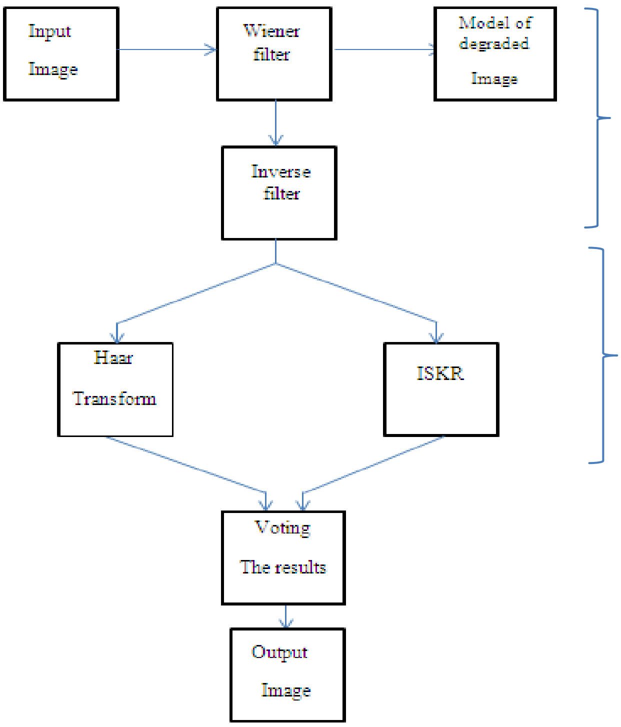

Figure (5): applied procedure and methods in this paper.

1. Steering Kernel Regression (ISKR):

Steering Kernel Regression (ISKR) is a regression process with nonlinear features. In this method, a kernel window with odd dimensions and a Gaussian function (or another proper function) as a kernel function are used for noise reduction inside an analysis window. The analysis window around the kernel window is applied to find regression coefficient based on two dimensional Taylor Series. InISKR it is sufficient to get the first coefficient of Taylor Series (β_0). Two of other coefficients (β_1, β_2) are applied as gradients around pixels inkernelwindow. Thencovariance of the gradients are calculated in a two dimensional square matrix. This helps us to get updated kernel function to be more sensitive to the edges. In (3) Y_i is a pixel value, z (x_i) is function of regressionandϵ_i is theadditive noise at theposition of x_i=[x_1,x_2].

$$Y_i = z(x_i) + \varepsilon_i \tag{3}$$

We have the N-th order Taylor series as mentioned in (4).

$$Z(x_i) \approx z(x) + \{\nabla z(x)\}^T (x-x_i) + 1/2\, (x_i - x)^T \{ H\, z(x)\}^T (x-x_i) + \dots \tag{4}$$
$$\approx \beta_0 + \beta_1^T (x_i - x) + \beta_2^T \mathrm{vech}\{(x_i-x)(x_i-x)^T\} + \dots$$

The kernel function is mentioned in (5). C_i is the covariance matrix of gradients and h, is bandwidth for the Gaussian function.

$$K_{Hi}(x_i - x) = \frac{\sqrt{\det(C_i)}}{2\pi h^2}\ 1/2h^2 \|C_i^{1/2}(x_i-x)\|_2^2\} \tag{5}$$

Covariance matrix can be written in circular Eigen matrices as mentioned in (6), where $\gamma_i$is scaling parameter, $U_{\theta i}$ is circular matrix and$\Lambda_{\sigma i}$ is elongation matrix.

$$C_i = \gamma_i U_{\theta i} \Lambda_{\sigma i} U_{\theta i}^T \tag{6}$$

The noise ridden pixels are mentioned in (7) that is equal to first coefficient of regression (β_0). In (7) e_1^T is a vector with first element equal to scalar 1 and others equal to scalar 0 and b, is matrix of regression coeffitence.

$$Z(x) = \beta_0 = e_1^T b = \Sigma\, W_i(K,H,N,x_i-x) y_i \tag{7}$$

If we use Steering Kernel Regression in a recursive way, we can adopt the kernel for more powerful enhancement.

2. Haar Wavelet Transform:

Unlike the Fourier transform that is based on sinusoids basis functions, Wavelet transform are based on small waves, called wavelets. Wavelet transform has the ability of save the temporal and frequency information of signals athwart Fourier transform that only considers frequency characteristics of signals. (8) Shows the Haar transform function, where H is transfer function and F is matrix of image.

$$T = HFH \tag{8}$$

Both of H and F matrices are square with dimension of N. In (9) and (10), Haar basis functions are shown.

$$1/\sqrt{N} \quad , \qquad z \epsilon [0,1] \tag{9}$$

$$1/\sqrt{N} = \begin{cases} 2^{p/2}, (q-1)/2^p < z < (q-0.5)/2^p \\ -2^{p/2}, (q-0.5)/2^p < z < q/2^p \\ 0 \text{ ,otherwise, } z \epsilon [0, 1] \end{cases} \tag{10}$$

h_k that used in (10) is depend on the values of p and q. K is also calculated by p and q from the integers of 1 to N-1. The value of q is related to the value of p and the value of p is chosen from integers of 1 to n-1. In (11) the relations between p, q and k are shown.

$$\begin{cases} K=0,1,\ldots,N-1 \\ N = 2^{n} \\ K=2^{p}+q-1 \\ 0<p<n-1 \\ q = \begin{cases} 0 \text{ or } 1 & p=0; \\ 1<q<2^{p} & p=0; \end{cases} \end{cases} \quad (11)$$

IV. Experimentsandresults

The results of the proposed algorithm are evaluated in term of visual and statistical approaches. We also will compare the results of two methods used in enhancementof outputs. In addition, MATLAB software Softwarehave been used for implementation and comparison results.

1. Wild Database:

Wild database contains images, taken during years 2002 and 2003, in four types of atmospheric conditions: haze, cloud, fog and clear weather. The images were provided by Dr. S.G. Narasimhan and Dr. S.K. Nayar at Columbia University and are in two different resolutions of (1532160) and (95760) pixels.

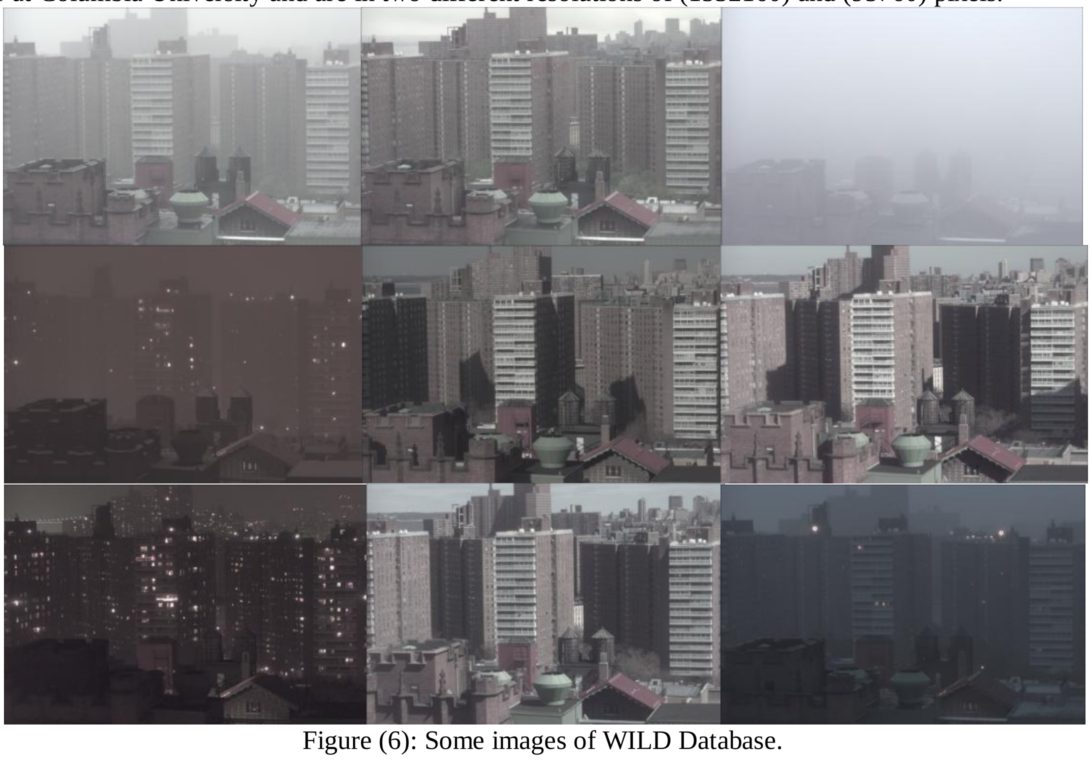

Figure (6): Some images of WILD Database.

In figures (7, 9) the results of experiments on sample hazy images, in different times of day are shown. In figure (7), R and γ are equal to 1 and 2.4 but, in figure (9) the values are equal to 0.9 and 2.9, because of difference in PSF functions and improving the brightness in figure (9).

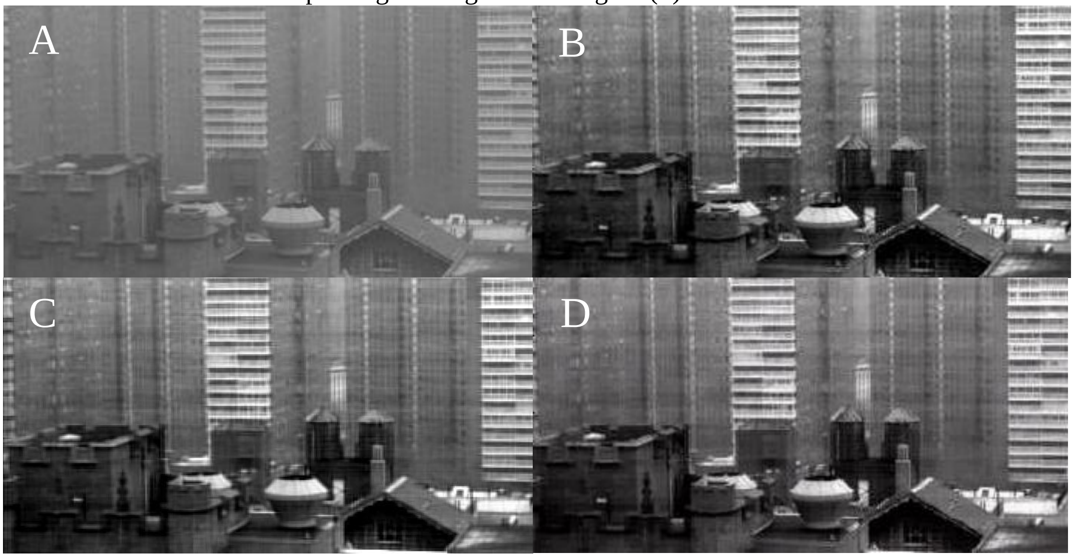

Figure (7):Hazy, Restored and Enhanced images, A: input image from WILD database [11], B: Restored image by inverse filter, C: Enhanced image by ISKR, D: Enhanced image by Haar Wavelet transform.

Wiener filter in this paper is not only a tool to remove the effect of haze, but also it is used for improving the brightness and distance estimation. According Morgan table sample size [15], it is sufficient for the size of between 75,000 to 1,000,000 pixels to take a sample of 382 pixels and then check the normality of residuals. The normality of residuals distribution was investigated and illustrated in figure (8).

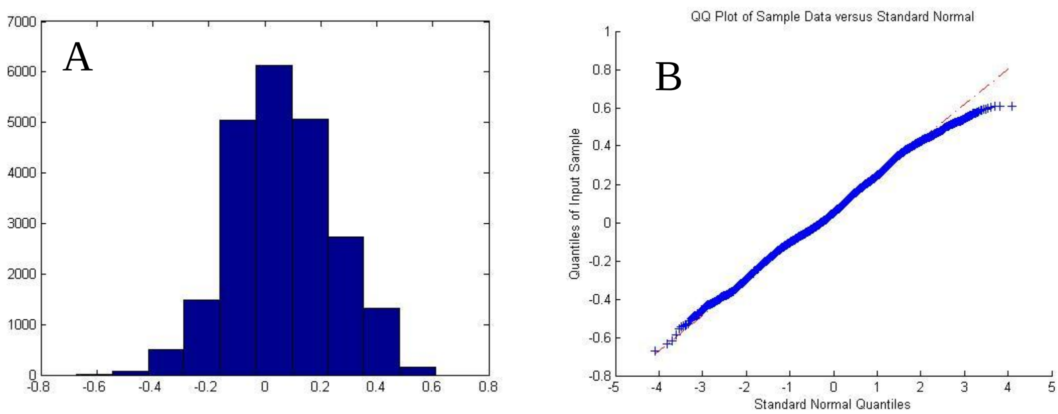

Figure (8): residuals of output image for a sample with 382 pixels, A: Histogram, B: Q-QPlot.

As we can see in Figure (8) the distribution of residuals tends to be normal. Q-Q plot is a graphical approach to show the similarity of two distributions. The line y=x is a factor that can help us to see how much the distributions are the same. In anidealresult, itis expected to see the points are exactly lied on the y=x line.

In Figure (9), the proposed method was applied to an image, provided in a hazy night. It is supposed that Wiener filter can also improve darkness or extra brightness in images.In color images this method can be used for each channel separately. Of course as natural images are used in this paper, it is not expected that the normality of errors (noise) and also residuals. Totally, Wiener filter is always applied with the prior assumption of normal distribution for the noise that also has zero mean. in the natural experiments the noise distributions always change for different images.

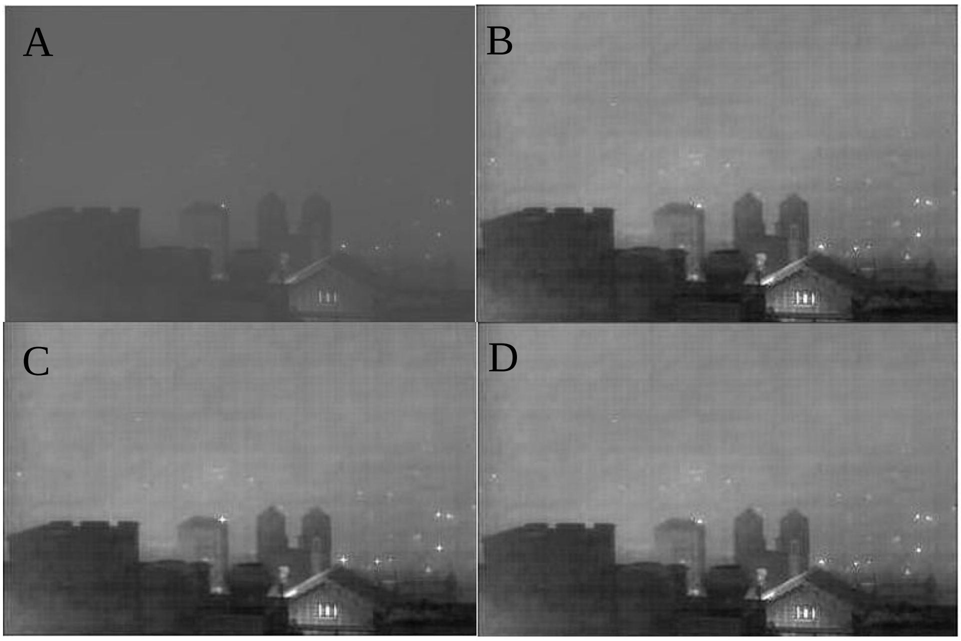

Figure (9): Hazy, Restored and Enhanced images, A: input image from WILD database [11], B: Restored image by inverse filter, C: Enhanced image by ISKR, D: Enhanced image by Haar Wavelet transform.

2. Comparing results of applied enhancement methods:

In this section we tried to make a comparison between the results of enhancement done by ISKR and Wavelet Transform around the outputs of our algorithm. To achieve this goal we have asked from 30 students of IAUCTB to tell us their opinion about the results of figure (7). First before doing any enhancement, 27 individuals claimed that the noise reduction by the inverse filter is satisfactory. In second step, we asked them again to tell us their idea about the results of two applied enhancement methods respectively. Among 30 students 18 students claimed that ISKR has improved the input image, when we asked them about the successfulness of Haar Wavelet transform in figure (7), 29 students claimed that the results are acceptable. SPSS software was used to compare means of the positive answers. As it is shown in figure (10), Wavelet transform had better role in enhancement of output of the inverse filter.

T-Test

Paired Samples Statistics

		Mean	N	Std. Deviation	Std. Error Mean
Pair 1	INVERSE	.8667	30	.34575	.06312
	ISKR	.6000	30	.49827	.09097
Pair 2	INVERSE	.8667	30	.34575	.06312
	WEVELET	.9667	30	.18257	.03333

Paired Samples Correlations

		N	Correlation	Sig.
Pair 1	INVERSE & ISKR	30	.480	.007
Pair 2	INVERSE & WEVELET	30	.473	.008

Paired Samples Test

		Paired Differences					t	df	Sig. (2-tailed)
		Mean	Std. Deviation	Std. Error Mean	95% Confidence Interval of the Difference				
					Lower	Upper			
Pair 1	INVERSE - ISKR	.26667	.44978	.08212	.09872	.43462	3.247	29	.003
Pair 2	INVERSE - WEVELET	-.10000	.30513	.05571	-.21394	.01394	-1.795	29	.083

Figure (10): Mean analysis by SPSS software.

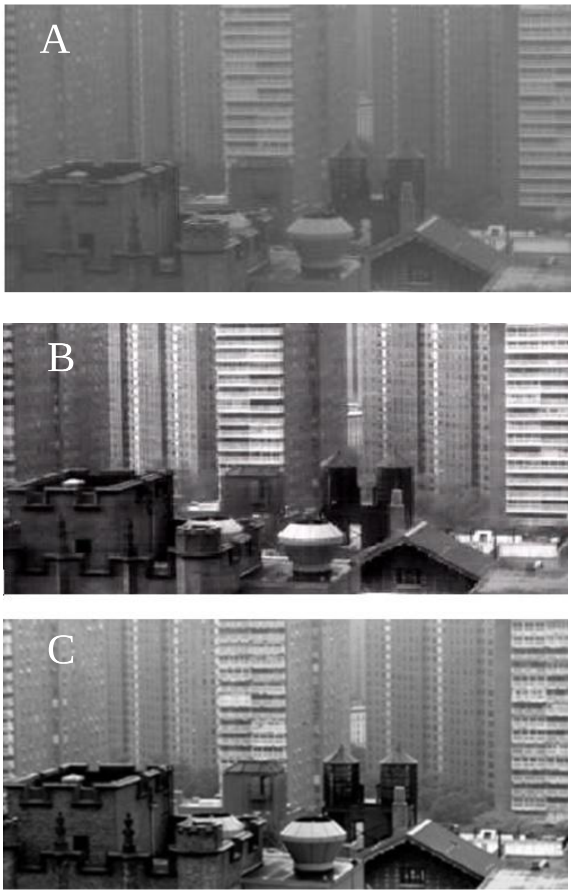

Figure (10): Hazy, Restored and Enhanced images, A: input image from WILD database [11], B: the proposed algorithm, C: restored by depth estimation algorithm[1].

In figure (10), the outputs of two different algorithms (the algorithm in [1] and our proposed algorithm), were shown. Both algorithms have the ability of real-time implementation, but the most important benefit of our proposed method is the needlessness to the prior measurements of physical conditions in the bad atmosphere such as total scattering coefficient$\beta(\lambda)$ for depth estimation.

V. Conclusion

In the natural experiments there is no priorinformation about distribution of accidental events. By assumption of normal distribution of natural hazy images, we tried to remove haze by Wiener filter and an Inverse filter, without the need of former information about the physical atmosphericconditions and distance estimation. Furthermore, for the improvement of the output images, we used two methods of ISKR and Haar Wavelet transform for enhancement of the restored images. By voting among30studentsof IAUCTB and their opinions, we havefound out thatHaar Wavelet transform is more successful in enhancing restored images form our applied inverse filter. The method that we proposed has the ability of real-time implementation and also in comparison to the other usual methods, doesn't need any prior information about physical conditions of the particles those exist in the bad weather.

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