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Experimental Implementation Of Image Restoration Schema Using Inverse Filter Processing Techniques

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Abstract-Image Restoration in Image processing domain provides the analytical way of implementation towards real-time data with different level of implications. Our experimental setup initially focuses with images with blurring and noises. This paper perform a detailed study of inverse filter schema towards variant effect of noisy blurred images in the field of image processing which can be carried out with expected optimal output strategies. We will implement our experimental image restoration techniques with real time implementation of object representation in the motive of advertisement Domains such as an image clarity required for a sweet stall in Tirunelveli District. We will also perform algorithmic procedural strategies for the successful implementation of our proposed research technique in several sampling domains with a maximum level of improvements. In near future we will implement the Optimal Image Restoration techniques for the de noising structure of images domain.

I.Introduction

Image filter plays an vital role in image processing techniques .The proper usage of filters can produce an optimal level of expected image implications.

Image Filter:

The image method of filter design determines the properties of filter sections by calculating the properties they have in an infinite chain of such sections. In this, the analysis parallels transmission line theory on which it is based. Filters designed by this method are called *image parameter filters*, or just *image filters[1]*. An important parameter of image filters is their image impedance, the impedance of an infinite chain of identical sections.The basic sections are arranged into a ladder network of several sections, the number of sections required is mostly determined by the amount of stopband rejection required. In its simplest form, the filter can consist entirely of identical sections. However, it is more usual to use a composite filter of two or three different types of section to improve different parameters best addressed by a particular type[2]. The most frequent parameters considered are stopband rejection, steepness of the filter skirt (transition band) and impedance matching to the filter terminations.

Image filters are linear filters and are invariably also passive in implementation.

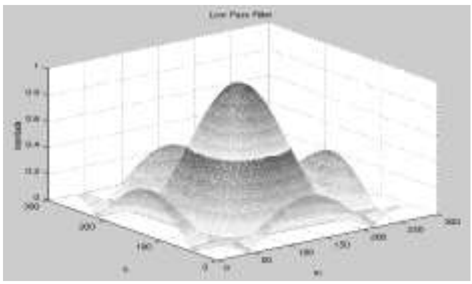

Figure-1; Low Pass filter

Image noise is random (not present in the object imaged) variation of brightness or color information in images, and is usually an aspect of electronic noise. It can be produced by the sensor and circuitry of ascanner or digital camera. Image noise can also originate in film grain and in the unavoidable shot noise of an ideal photon detector. Image noise is an undesirable by-product of image capture that adds spurious and extraneous information.

The original meaning of "noise" was and remains "unwanted signal"; unwanted electrical fluctuations in signals received by AM radios caused audible acoustic noise ("static"). By analogy unwanted electrical fluctuations themselves came to be known as "noise".[3] Image noise is, of course, inaudible. The magnitude of image noise can range from almost imperceptible specks on a digital photograph taken in good light, to optical and radioastronomical images that are almost entirely noise, from which a small amount of information can be derived by sophisticated processing (a noise level that would be totally unacceptable in a photograph since it would be impossible to determine even what the subject was).

An image is a picture, photograph or any other form of 2D representation of any scene.[10] Most algorithms for converting image sensor data to an image, whether in-camera or on a computer, involve some form of noise reduction. There are many procedures for this, but all attempt to determine whether the actual differences in pixel values constitute noise or real photographic detail, and average out the former while attempting to preserve the latter. However, no algorithm can make this judgment perfectly, so there is often a tradeoff made between noise removal and preservation of fine, low-contrast detail that may have characteristics similar to noise. Many cameras have settings to control the aggressiveness of the in-camera noise reduction[4].

A simplified example of the impossibility of unambiguous noise reduction: an area of uniform red in an image might have a very small black part. If this is a single pixel, it is likely (but not certain) to be spurious and noise; if it covers a few pixels in an absolutely regular shape, it may be a defect in a group of pixels in the image-taking sensor (spurious and unwanted, but not strictly noise); if it is irregular, it may be more likely to be a true feature of the image. But a definitive answer is not available[5].

This decision can be assisted by knowing the characteristics of the source image and of human vision. Most noise reduction algorithms perform much more aggressive chroma noise reduction, since there is little important fine chroma detail that one risks losing. Furthermore, many people find luminance noise less objectionable to the eye, since its textured appearance mimics the appearance of film grain.[9]

The high sensitivity image quality of a given camera (or RAW development workflow) may depend greatly on the quality of the algorithm used for noise reduction. Since noise levels increase as ISO sensitivity is increased, most camera manufacturers increase the noise reduction aggressiveness automatically at higher sensitivities. This leads to a breakdown of image quality at higher sensitivities in two ways: noise levels increase and fine detail is smoothed out by the more aggressive noise reduction[6].

In cases of extreme noise, such as astronomical images of very distant objects, it is not so much a matter of noise reduction as of extracting a little information buried in a lot of noise; techniques are different, seeking small regularities in massively random data.

Image processing usually refers to digital image processing, but opticaland analog image processing also are possible[3] This article is about general techniques that apply to all of them. The *acquisition* of images (producing the input image in the first place) is referred to as imaging[7].

Closely related to image processing are computer graphics andcomputer vision. In computer graphics, images are manually *made* from physical models of objects, environments, and lighting, instead of being acquired (via imaging devices such as cameras) from *natural* scenes, as in most animated movies. Computer vision, on the other hand, is often considered *high-level* image processing out of which a machine/computer/software intends to decipher the physical contents of an image or a sequence of images (e.g., videos or 3D full-body magnetic resonance scans)[5].

Image restoration is the operation of taking a corrupted/noisy image and estimating the clean original image. Corruption may come in many forms such as motion blur, noise, and camera misfocus.Image restoration is different from image enhancement in that the latter is designed to emphasize features of the image that make the image more pleasing to the observer[7], but not necessarily to produce realistic data from a scientific point of view. Image enhancement techniques (like contrast stretching or de-blurring by a nearest neighbor procedure) provided by "Imaging packages" use no a priori model of the process that created the image [8].

II. Proposed Methodology-The Imaging model

The image restoration can be achieved by applied an inverse filter $\frac{1}{\widehat{\mathbf{H}}(\mathbf{u},\mathbf{v})}$ to the observed blurry image, i.e.,

$$\widehat{\mathbf{O}}(\mathbf{u},\mathbf{v}) = \frac{\mathbf{I}(\mathbf{u},\mathbf{v})}{\widehat{\mathbf{H}}(\mathbf{u},\mathbf{v})}$$

Theoretically, the inverse filter is the inverse of the degradation function. However, if this was implemented, the inverse filter will enlarge the high frequency noise. This is due to that most degradation function have low-pass filter nature, hence, it has relatively low high frequency power spectrum. If an inverse operation is performed, the inverse filter will have a high-pass filter nature, which will cause the blurred image to have a magnified high frequency noise.

Therefore, the actual implementation of inverse filter will need to consider the nature of the degradation function and blurred image function, i.e.,

$$\widehat{\mathbf{H}}(\mathbf{u},\mathbf{v}) = \begin{cases} \frac{\mathbf{1}}{\mathbf{H}(\mathbf{u},\mathbf{v})}, & |\mathbf{H}(\mathbf{u},\mathbf{v})| \geq \alpha \\ \mathbf{0}, & |\mathbf{H}(\mathbf{u},\mathbf{v})| < \alpha \end{cases}$$

where α is a threshold that is used to mitigate the effect of zeros in the degradation function

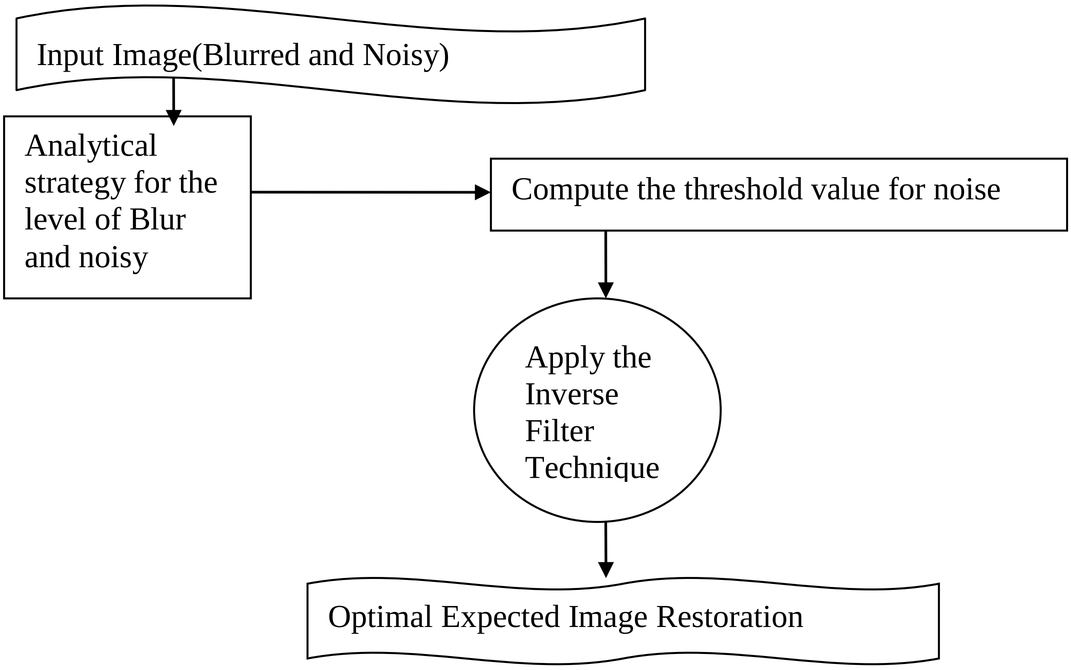

Figure 2: Proposed Image restoration Procedure

III.IMPLEMENTATION

The Matlab code for the implementation of Inver filter strategical technique is as follows,

```
freq = 104.98;  % estimated peak frequency in Hz
bw = 10;        % peak bandwidth estimate in Hz
R = exp( - pi * bw / fs);            % pole radius
z = R * exp(j * 2 * pi * freq / fs); % pole itself
B = [1, -(z + conj(z)), z * conj(z)] % numerator
r = 0.9;     % zero/pole factor (notch isolation)
A = B .* (r .^ [0 : length(B)-1]);   % denominator
residual = filter(B,A,bodyIR); % apply inverse filter.
```

Now implementing the proposed restoration technique the input image can be restored as follows,

Figure:-3 Input Image

Figure:-4 Iteration-1 DeBlur Most noise

Figure:-5 Iteration-9 with DeBlur Less Noise

Figure:-6 Iteration-14-deblur Least Noise

The following table illustrates the proposed methodology implementation for the image restoration process.

Table 1:Image Restoration Levels

Sl.No	Image Restore-Level	Blur level	Noise level	Image restoration level
1	Iteration-1	50%	40%	55%
2	Iteration-2	40%	50%	55%
3	Iteration-9	30%	40%	65%
4	Iteration-14	5%	10%	92.5%
5	Iteration-17	3%	8%	94.5%
6	Iteration-18	2%	5%	96.5%
7	Iteration-20	2%	5%	96.5%

IV.RESULTS AND DISCUSSIONS

The following graph illustrates the restoration improvent for implementing the proposed methodology.

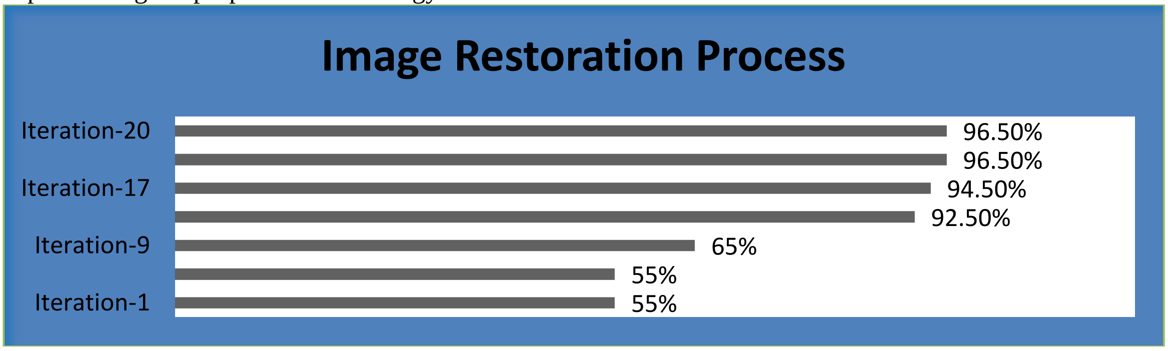

Figure-7 :Image Restoration process Graph

The setting of the threshold plays the vital role in our procedural approach which must satisfy the following $|H(u,v)| < \alpha$

This will be a positive integer in the range of 0 to 1. The pivotal value of α is, the faster $|H(u,v)|$ will converge. However, picking too large α may also make the noise level of the image increases rapidly wrt the reduced blurred degradation level. Imagine that the two different atrtributes of indirect proportional strategies without any proper combination will yield tha inappropriate results. Taking large steps will ensure that we will get there fast but we'd probably first. Taking small will ensure that we get there without falling off but it could take an infinite amount of time. So the compromise would be to take big steps at the start and decrease our step size as we get close to our destination.

The following is the optimal expected image after 18 iterations. α starts off at 0.1 and increases by 10% every individual iteration.

Figure-8 :Iteration-18 Optimal output Image

V.CONCLUSION

Handling images in an optimal or an expected form is a highly technical process to implement in an efficient way. The selection of image and the proper utilization of image processing tool is a scientific methodology to implement. Our proposed methodology make it as an easy process by the analytical view of blur level and noise level combinations, further focusing of their mutual proportion along with variational effects we achieved an restoration process with 96.5 % efficiency.. For a given image size, we are limited in the blur type and multiple noise resolutions. For multiple degraded images, we may be limited by how many image snapshots we can obtain. So we are limited in both cases by how many iterations we can average over, and this profoundly affects our estimations. This is one of the main drawbacks that we found in the combination sector of Blurrednoisy image restoration techniques.

In near future this research will focus on an optimal algorithmic identification of Universal Combination of Image restoration process.

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