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# Comparison between Blind Deconvolution of images using wavelet analysis and using Gabor filter & Independent Component Analysis

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**ABSTRACT** *: The image restoration is to estimate an original image from the image degraded by blurring and noise. The degrading process is usually modeled as a convolution of a Point Spread Function (PSF) with an original image. In this paper we compared two prominent methods of blind deconvolution. One uses wavelet analysis and second method uses Gabor filter & Independent Component Analysis (ICA). Method using wavelet analysis does not remove noise. Blind deconvolution using Gabor filter & Independent Component Analysis even though is complex, gives superior results as compared to wavelet analysis.*

**Keywords** – *Blind deconvolution, PSF, Gabor filter, Image Restoration*

## I.INTRODUCTION

In many applications, such as astronomy, remote sensing, medical imaging, military detection, public security and video technology, images are the main sources of information. But, due to some reasons, observed images are degraded. The degradations are mainly caused by blur and noise. The aim of image restoration is to obtain restored image which should be as close as possible to the original image.

The degrading process is usually modeled as a convolution of a Point Spread Function (PSF) with an original image and an additive noise.

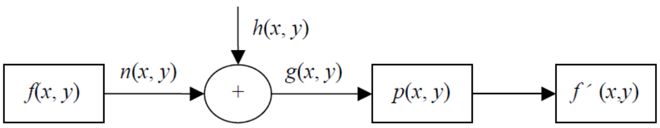


**Fig. 1 The model of image degradation & restoration**

The degraded image can be modeled by ;

$$g(x, y) = f(x, y) \otimes h(x, y) + n(x, y) \qquad (1)$$

Where $f(x, y)$ represents an original image and $g(x, y)$ is the degraded image. In the model $n(x, y)$ represents an additive noise introduced by the system, and $h(x, y)$ is the point spread function of the blur, whole $f'(x, y)$ and $p(x, y)$ are stored image and restoration system function, respectively. Where ⊗ stands for convolution. With the help of PSF, the image restoration can be divided into two types [3]

1. Non-blind deconvolution
2. Blind deconvolution

If a PSF is known in advance, it is called as Non-blind deconvolution. A lot of restoration algorithms, such as a Wiener filter and a generalized inverse filter, are proposed and the restoration method is almost established. The Wiener Filter can be used effectively when the frequency characteristics of the image and additive noise, are known, at least to some degree.

On the other hand, several restoration algorithms without using information about a PSF are also proposed. This kind of an algorithm restores an original image by simultaneously estimating an image and a PSF, and it is called a *blind deconvolution.*

In [1], an image restoration method for noisy image corrupted by additive white noise is proposed. It is well known that the Adaptive Wiener Filter (AWF) is suitable for such restoration. However, some noises remain in an image restored by the AWF. In order to improve the performance of the AWF, an iterative algorithm is proposed. To prevent original image signal loss, a weighting parameter is used for the noise.

Myopic deconvolution is used when PSF is partially known. In[2], the "myopic" deconvolution scheme is briefly presented. This approach takes into account the noise in the image, the imprecise knowledge of the point spread function (PSF), and the available a priori information on the object (spatial structure, positivity...).. Besides, a specific edge preserving object prior is proposed for the application to planetary-like objects.

An estimation of a PSF is not easy in general except, for example, the case as a blurring produced by an uniform and one-directional movement of a camera. Blind deconvolution was developed mainly for restoration of images in astronomy. This is because an image of an astronomical body (a star) should be a point in principle and this information is very useful as a priori constraint of the estimation[3].Another blind deconvolution method is *Super Resolution* . Super resolution is a method to estimate a signal from the band limited observation data and has been studied in the signal processing field.[3]

In [4] , robust edge detection method based on ICA is proposed. In the proposed method, a test image is first transformed by ICA basis functions, & then high frequency information can be extracted with the components of the selected basis functions. The gradient mask such as Prewitt, Sobel or Canny is typically used for edge detection in noisy images. The performance of these operators dergrades considerably as the noise level increases.
In [5], the Lucy – Richardson algorithm and the blind deconvolution algorithm should be effective algorithms applied to blind image restoration. But in experiments we find that it cannot obtain the satisfactory result with this algorithm only. The reasons are that there are large amount of noises existing in the degraded images and that the initially guessed PSF is not well. We need to process the degraded image before the restoration and analyze the degraded image to get more information. Therefore we study two approaches

1. Wavelet analysis
2. Gabor filter & ICA

## II.WAVELET ANALYSIS:

We mainly implement two kinds of preprocessing; the filtering in frequency domain and the gray transformation according to the histogram. For the sake of getting better effects, filtering can be implemented before applying wavelet analysis. Generally, since the edges and the noises correspond to the proportions of high frequency in the spectrum, the high frequencies are often dominated by the noises, and then low pass filtering can be considered to smooth the image and remove the noises.

The gray transformation can help us to restore the natural information of images and increase contrast. But it is very important to select the appropriate parameters for increasing contrast. In the experiments, we can infer the parameters from the histogram information of the degraded image, for example the gray level of peaks.

Image used in the experiment is the "Lena" image, as is shown in fig. 2(a). The image in Figure 2(b) is heavily degraded. First, the preprocess is implemented. Then, wavelet analysis is applied to the degraded image. After that, the PSF is restored based on the above work.

The images restored by conventional approaches and gray transformation are shown in figure 2(c), (d) respectively. From fig. 2 we find that the degraded image can be improved to a certain degree, though averting from the identification of the PSF. The contrast of image is increased and the details of images become outstanding.

The restored image in figure 3(a) is obtained by the Lucy algorithm. It is worth noting that the times of iteration in the Lucy algorithm should be selected carefully. Lucy algorithm perform iterations using optimization techniques and Poisson statistics, which not need information about the additive noises.
Furthermore, we can guess that the PSF may be a spatially invariant blurring PSF or a stationary PSF according to the well restored result by the Lucy algorithm.

The reason of poor performances by the other three methods may be that the initial guessed PSF is not well. To improve the restoration, we can adjust the PSF. One of the ways is Padarray. Hence, we use Blind Deconvolution method with the adjusted PSF to implement. The restored image is shown in the Figure 3 (b). Compared with unadjusted, the image become more clear, but still exist noises in the restored image.

(a ) (b) (c) (d)

**Fig. 2 Lenna image experiment** (a) Original image (b) Degraded image (c) Image restored by classical approach directly (d) Restored image based on gray transformation

(a) (b) (c) (d)

**Fig. 3 Lenna image experiment** (a) Restored image by lucy algorithm with wavelet analysis (b) Restored image by adjusted PSF (c) Restored image by combined approach (d) Final restored image based on gray transformation & filtering

In order to further optimization, we use combined restoration approach to implement. The restored images are shown in the fig. 3(c). As expected, the results are obviously improved. Most of noises are removed and the image becomes smooth. It is worth noting not all the combined approaches can obtain better restoration results. The selection and the order of combined approaches should be implemented according to practical case.

It is necessary to implement the gray transformation and filtering again to guarantee the better results. The final result is shown in fig. 3(d).

Even though obvious improvement is obtained by our method in the experiments, there are still some artifacts in restored images. The most prevalent artifacts are ringing around the edges and Gibbs effect in the restored image. The ringing artifacts are dependent on the blur operator and the restoration filter, and the given image (6). The Gibbs effect caused by the shift variant characteristic of wavelet transformation (7). Ringing and Gibbs effect are very obvious in fig. 3(c). In order to remove the artifacts, we implement gray transformation and filtering again after the restoration as above described. The obtained result is shown in fig. 3(d). As we can see, artifacts are reduced, whereas the effects of noises still exist.

## III.GABOR FILTER & ICA

They realize multichannel filtering which decompose an input image into a number of filtered images. Each filtered image contains intensity variation over a narrow range of frequency and orientation.

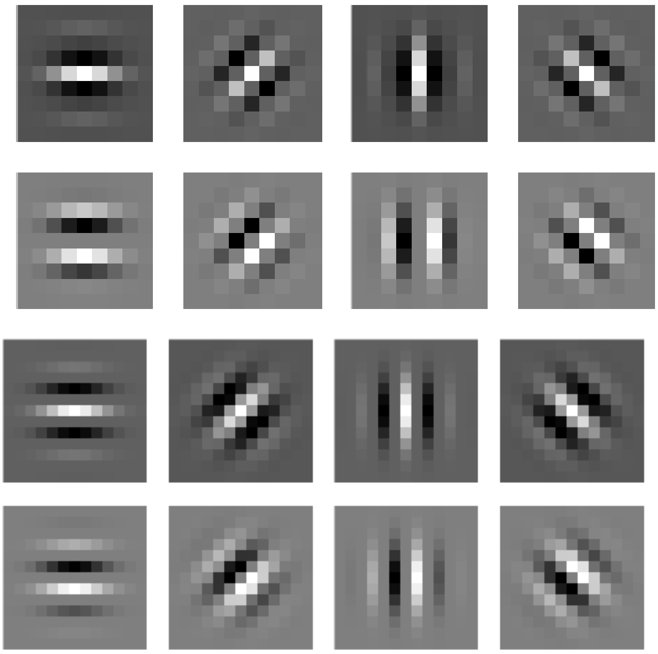

**Fig. 4 Gabor Filters**

The 2D Gabor filter is defined as a complex function, and its real and imaginary part are used as two real filters. The following equations show 2D Gabor filters.

$$R(x,y;\nu,k) = \exp\left(-\frac{x^2+y^2}{2\sigma_\nu^2}\right) \cdot \cos\frac{\pi}{\sigma_\nu}(x\cos\phi_k + \sin\phi_k) \quad (2)$$

$$I(x,y;\nu,k) = \exp\left(-\frac{x^2+y^2}{2\sigma_\nu^2}\right) \cdot \sin\frac{\pi}{\sigma_\nu}(x\cos\phi_k + \sin\phi_k) \quad (3)$$

where

$$\sigma_\nu = (\sqrt{2})^{\nu+1} \quad (4)$$

$$\phi_k = \frac{\pi}{4}k \quad (5)$$

In the following experiments we set $\nu \in \{0,1\}$ and $k \in \{0,1,2,3\}$ as parameters, thus we use total 16 Gabor filters.

Fig.4 shows these filters as images. The upper two rows of Fig.4 are filters of v=0 ,and the lower two rows are filters of v=1.The first and third rows of images show Gabor filters corresponding to a real part, and simulate the response of a simple neuron with a line detection ability. On the other hand, the second and fourth rows show Gabor filters corresponding to an imaginary part, and simulate the response of a simple neuron with a edge detection ability   We use the Gabor filters in this paper for two reasons. The first is that since the Gabor filters are similar to the first and second order differential filters, the output of the filters should be close to the first and the second derivative images.

The restoration model above assumes the original image and its derivative images as independent components, thus we judged that the Gabor filters are suitable for the method. The second reason is that the hierarchical structure (Fig.4) of the Gabor filters may be useful for various degrees of blurring.

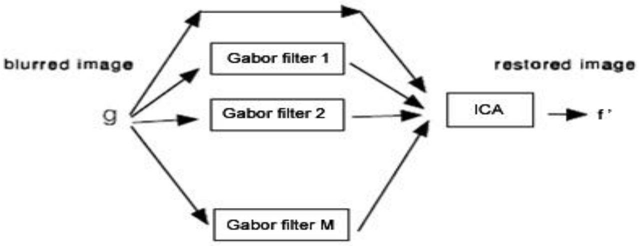


**Fig. 5 Restoration by ICA & Gabor filters**

## IV. ICA ALGORITHM :

First the images (the blurred image and the output images of the Gabor filters) are transformed into vectors..by scanning them left-to-right and top-to-bottom manner. Here we center the data to make its mean zero. Then the data matrix. is given as follows,

$$X = \begin{bmatrix} g_1^T \\ g_2^T \\ \cdots \end{bmatrix}. \quad (6)$$

The element $y_j$ of the first independent component $y$ is given as the inner product of the weight vector $w$ and the whitened data $z_j$.

$$y_j = w^T z_j \quad (7)$$

## V. BASIC EXPERIMENT :

The image shown in Fig. 6(a1) was used as the original image. The size of the image is 160 x 160. Fig. 6(a2) and (a3) show the x-derivative and y-derivative images of the original image. The blurred image was created by applying a Gaussian filter to the original image. The parameters of the Gaussian filter were set as σx=1 and σy=1. We call this filter G (1,1).

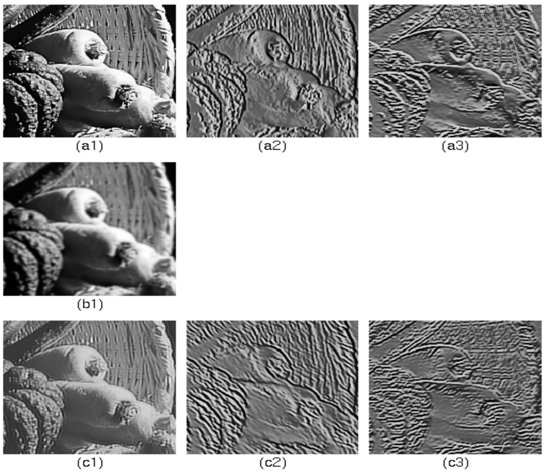


**Fig. 6 Blind deconvolution results**

The obtained blurred image is shown in Fig.6 (b1). Gabor filters shown in Fig.4 were applied to it, and the output images of the filters and the original blurred image were fed to ICA & independent components were estimated.

Fig.6(c1), (c2) and (c3) are obtained independent components which have high correlations with the original image (Fig.6(a1)), x_-derivative image (Fig.6(a2)) and y-derivative image (Fig.6(a3)). The correlation coefficients with the original images are 0.967, 0.721, and 0.791, respectively. The correlation coefficient between the blurred image (Fig.6(b1)) and the original image is 0.920. This experiment shows that the proposed method gives a good restoration result (0.920→ 0.967) even when the blurring process is unknown, and ICA gives not only the original images but its derivative images as the restoration model supposes.

## VI. CONCLUSION

In this paper, we have compared both the techniques, blind deconvolution by using wavelet analysis and gabor filter & ICA. We have observed that even though wavelet analysis offers a simpler method for deconvolution, the method is not capable of removing noise. On the other hand deconvolution using gabor filter & ICA gives much better results as compared to wavelet analysis.

## REFERENCES

1. Chikako Abe, Tetsuya Shimamura (Saitama Univ.), “Iterative Edge-Preserving Adaptive Wiener Filter for Image Restoration” *IEICE Tech. Rep., vol. 109, no. 226, SIP2009-60, pp. 23-28, Oct. 2009*
2. Jean-Marc Conan, Thierry Fusco, Laurent M. Mugnier, Evy Kersal´e and Vincent Michau, “Deconvolution of adaptive optics images with imprecise knowledge of the point spread function: results on astronomical objects”, *Office National d’´Etudes et de Recherches A´erospatiales (ONERA),D´epartement d’Optique Th´eorique et Appliqu´ee,BP 72, F-92322 Chˆatillon cedex, France*
3. Shinji Umeyama, “Blind Deconvolution Of Images Using Gabor Filters And Independent Component Analysis”,*ICA2003,Nara,Japan*
4. “A robust method based on ICA for edge detection in medical images”, *Springer Verlog London Limited, DOI 10.1007/s11760-009-0140-5*
5. Dong-Dong Cao,Ping Guo“Blind image restoration based on wavelet analysis” *International conference on machine learning and cybernetics,Guangzhou,August 2005*
6. Mark R. Banham, and Aggelos K. katsaggelos, “Digital Image Restoration”,*IEEE Signal Processing Magazine,pp.24-41 March 1997*
7. Coifman RR, and Donoho DL, “Translation-Invariant denoising”,*Springer-Verlag,1995*