Motion Blur Image Fusion Using Discrete Wavelate Transformation

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Abstract

The methodology for implementing a image fusion system using deconvolution and discrete wavelate transformation is proposed in this papers. This project proposes a method to remove the motion blur present in the image taken from any cameras. The blurred image is restored using Blind de-convolution method with N=20 number of iteration and DWT using averaging, maximum likelihood and window based method.the comparision result of both the method prove that image restoration using dwt gives better result than image restoration using deconvolution.

Keywords: multisensory system,pyramid transform,discrete wavelet transform,Motion blur,blind deconvolution,

1. Introduction

With the recent rapid developments in the field of sensing technologies multisensory systems[1,2] have become a reality in a growing number of fields such as remote sensing, medical imaging, machine vision and the military applications for which they were first developed. The result of the use of these techniques is a great increase of the amount of data available. Image fusion provides an effective way of reducing this increasing volume of information while at the same time extracting all the useful information from the source images. Multi-sensor images often have different geometric representations, which have to be transformed to a common representation for fusion. This representation should retain the best resolution of either sensor. A prerequisite for successful in image fusion is the alignment of multi-sensor images. Multi-sensor registration is also affected by the differences in the sensor images.However, image fusion does not necessarily imply multi-sensor sources, there are interesting applications for both single-sensor and multi-sensor image fusion, as it will be shown in this paper.The primitive fusion schemes perform the fusion right on the source images.One of the simplest of these image fusion methods just takes the pixel-by-pixel gray level average of the source images. This simplistic approach often has serious side effects such as reducing the contrast. With the introduction of pyramid transform in mid-80's[3], some sophisticated approaches began to emerge. People found that it would be better to perform the fusion in the transform domain. Pyramid transform appears to be very useful for this purpose. The basic idea is to construct the pyramid transform of the fused image from the pyramid transforms of the source images, and then the fused image is obtained by taking inverse pyramid transform. Here are some major advantages of pyramid transform:

- It can provide information on the sharp contrast changes, and human visual system is especially sensitive to these sharp contrast changes.
- It can provide both spatial and frequency domain localization There are many transformations which can be used but Basically this paper makes the contribution of the two important transformation .

2. Discrete Wavelet Transformation(DWT)

The wavelet transform[4,7], originally developed in the mid 80's, is a signal analysis tool that provides a multi-resolution decomposition of an image in a bi orthogonal basis and results in a non-redundant image representation. These bases are called wavelets, and they are functions generated from one single function, called mother wavelet, by dilations and translations. Although this is not a new idea, what makes this transformation more suitable than other transformations such as the Fourier Transform or the Discrete Cosine Transform, is the ability of representing signal features in both time and frequency domain.Fig.1 shows an implementation of the discrete wavelet transform. In this filter bank, the input signal goes through two one-dimensional digital filters. One of them, H_0, performs a high pass filtering operation and the other H_1 a low pass one. Each filtering operation is followed by sub sampling by a factor of 2. Then, the signal is reconstructed by first up sampling, then filtering and summing the sub bands.

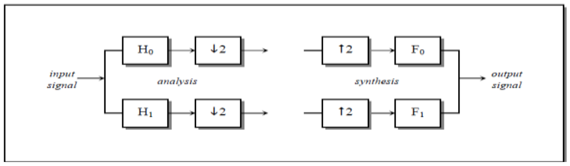


Figure 1.two channel filter bank

The synthesis filters F_0 and F_1 must be specially adapted to the analysis filters H_0 and H_1 to achieve perfect reconstruction [3]. By considering the z-transfer function of the 2-chanel filter bank shown in Fig.1 it is easy to obtain the relationship that those filters need to satisfy. After analysis, the two subbands are:

$$\frac{1}{2}\left[H_{0\left(z^{1/2}\right)}X\left(z^{1/2}\right)+H_{0\left(-z^{1/2}\right)}X\left(-z^{1/2}\right)\right] \qquad (1)$$

$$\frac{1}{2}\left[H_{0\left(z^{1/2}\right)}X\left(z^{1/2}\right)+H_{0\left(-z^{1/2}\right)}X\left(-z^{1/2}\right)\right] \qquad (2)$$

Then, the filter bank combines the channels to get $\hat{x}(n)$. In the z-domain this is $\hat{X}(z)$. Half of the terms involve $X(z)$ and half involve $X(-z)$.

$$X^{\wedge}(z)=\frac{1}{2}\left[F_0(z)H_0(z)+F_1(z)H_1(z)\right]X(z)+$$
$$\frac{1}{2}\left[F_0(z)H_0(-z)+F_1(z)H_1(-z)\right]X(-z) \qquad (3)$$

There are two factors to eliminate: aliasing and distortion. For alias cancellation choose:

$$F_0(z)=H_1(-z)$$
$$F_1(z)=H_0(-z) \qquad (4)$$

The distortion must be reduced to a delay term, to achieve this Smith and Barnwell suggested [8]:

$$H_1(z)=-z^{-N}H_0(-z^{-1}) \qquad (5)$$

With these restrictions the final filtering equation is

$$X(Z)=\frac{1}{2}z^{-N}\left[H_0(z)H_0(z^{-1})+H_0(z^{-1})H_0(z)\right]X(z) \qquad (6)$$

Fig.2 represents one step in a multiscale pyramid decomposition of an image [3]. The algorithm applies a one-dimensional high and low pass filtering step to the rows and columns separately in the input image. The inverse transform filter bank structure is represented in Figure 4.

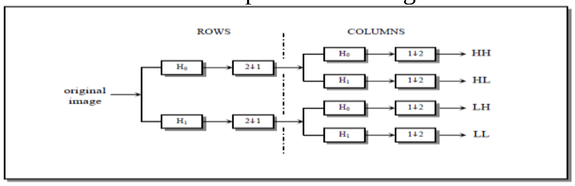


Figure 3 filter bank structure of DWT analysis

Successive application of this decomposition to the LL sub band gives rise to pyramid decomposition where the sub images correspond to different resolution levels and orientations as exemplified in Fig.5. Some images decomposed with the wavelet transform are shown in figure.6

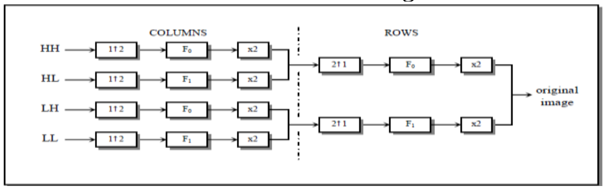


Figure 4 filter bank structure of the reverse DWT synthesis

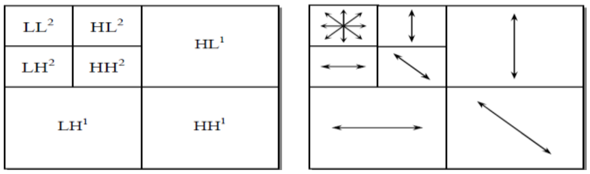


Figure 5 Image decomposition. Each sub band has a natural orientation

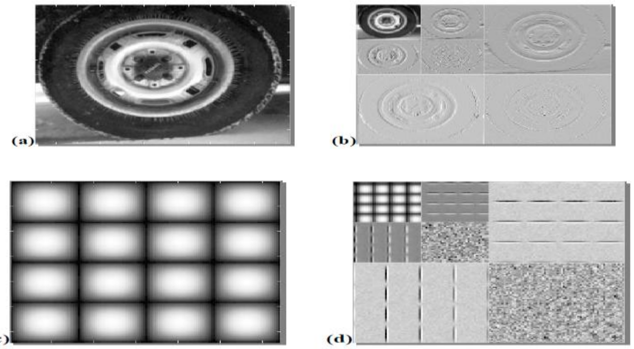


Figure 6 Images (a) and (c) shows original images and (b) and (d) their wavelet decomposition

3. Blind deconvolution

3.1_Proposed Method

Restoration techniques [1,5] are oriented toward modeling the degradation and applying the inverse process in order to recover the original image. The image gets blurred due to the degradation. Blur is of many types but for this paper motion blur is considered.

3.2_Block Diagram

Fig. 7 shows the block diagram of the proposed method[1]. In the original image noise is added to get blurred noisy image. To remove motion blur, the blurred image is restored using restoration algorithms. Finally the filtered Images are fused using image fusion method to get the fused image.

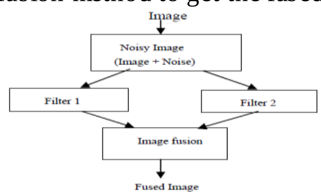


Figure 7 Block diagram

3.3 Noise model

Generally the noise is modeled as zero mean white Gaussian additive noise. But here we have modeled noise as sum of the multiplicative noise and additive Gaussian noise as

$v(x, y) = f(x, y)*\sigma 1(x, y)+ \sigma 2(x, y)$ (7)

Where $\sigma 1(x, y)$ is the multiplicative noise and $\sigma 2(x, y)$ is the additive noise.

3.4 Image restoration

In order to remove motion blur, various image restoration algorithms have been proposed. Blind deconvolution adopts regularized iteration to restore the degraded image. But it requires large computational complexity. For this reason, the work proposes the implementation of wiener filter to reduce the computational complexity with better acceptable restoration results of image restoration method.

3.5 Point Spread Function (PSF)

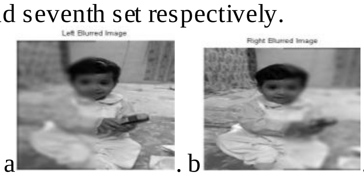
The General form of motion blur function [6] is given as follows,

$$h(x,y) = \begin{cases} \frac{1}{L}, & \text{if } \sqrt{x^2+y^2}\frac{L}{2}, \frac{x}{2} = -\tan(\emptyset) \\ 0, \ otherwise \end{cases} \quad (7)$$

As seen that motion blur function depends on two parameters: motion length (L) and motion direction (ϕ).

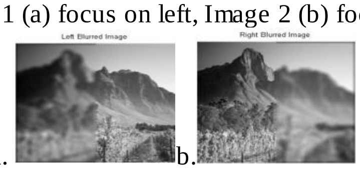
4. Fusion Techniques

In this research, two fusion approaches have been developed. These two approaches are the blind deconvolution & the discrete Wavelet Transform. These two methods, were selected for being the most representative approaches, especially the approach based on the Wavelet Transform has became the most relevant fusion domain in the last years. This section describes the technique specifications, their implementation and presents experimental results and conclusions for each of them. It is important to note that all the source images used in this research were already correctly aligned on a pixel-by-pixel basis, a prerequisite for successful image fusion. The fusion techniques have been tested with four sets of images, which represent different possible applications where fusion can be performed. The first set of images, Figure 10 called 'kid' represent the situation where, due to the limited depth-of-focus of optical lenses in some cameras, it is not possible to get an image which is in focus everywhere. The second set of images, Figure 11 corresponds to navigation . In this case, a millimeter wave sensor is used in combination with a visual image. An example of fusion applied to medicine is represented in the third set of images, Figure 12. One of the images was captured using a nuclear magnetic resonance (MR) and the other using a computed tomography (CT).Remote sensing is another typical application for image fusion. The fourth set of images in figure 13 illustrates the captures of two bands of a multispectral scanner. The purposes of them are navigation applications and surveillance applications for the sixth and seventh set respectively.



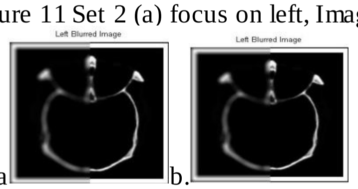
a. b.

Figure 10 Set 1 (a) focus on left, Image 2 (b) focus on right



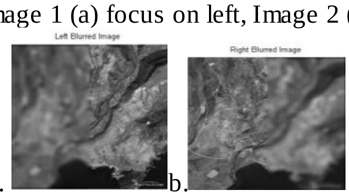
a. b.

Figure 11 Set 2 (a) focus on left, Image



a b.

Figure 12 Set 3. Image 1 (a) focus on left, Image 2 (b) focus on right



a. b.

Figure 13 Set 4. Image 1 (a) and Image 2 (b) multispectral scanner

4.1 Technique

An alternative to fusion using pyramid based multi resolution representations is fusion in the wavelet transform domain. As mentioned in *section II*. The wavelet transform decomposes the image into low-high, high-low, high-high spatial frequency bands at different scales and the low-low band at the coarsest scale. The L-L band contains the average image information whereas the other bands contain directional information due to spatial orientation. Higher absolute values of waveletcoefficients in the high bands correspond to salient features such as edges or lines.

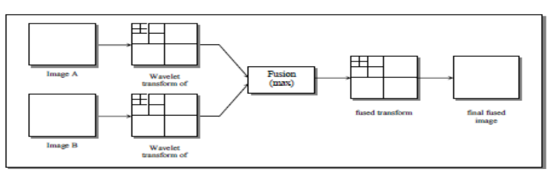


Figure 14.wavelet fusion scheme

Wavelet transform is first performed on each source images, and then a fusion decision map is generated based on a set of fusion rules as shown in figure 14. The fused wavelet coefficient map can be constructed from the wavelet coefficients of the source images according to the fusion decision map. Finally the fused image is obtained by performing the inverse wavelet transform. From the above diagram, we can see that the fusion rules are playing a very important role during the fusion process. Here are some frequently used fusion rules in the previous work as shown in figure 15.

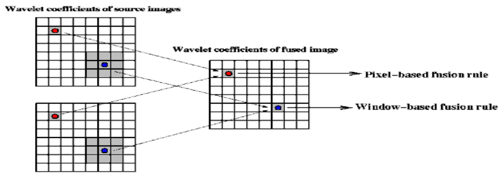


Figure 15.Frequently used fusion rules

When constructing each wavelet coefficient for the fused image. We will have to determine which source image describes this coefficient better. This information will be kept in the fusion decision map. The fusion decision map has the same size as the original image. Each value is the index of the source image which may be more informative on the corresponding wavelet coefficient. Thus, we will actually make decision on each coefficient. There are two frequently used methods in the previous research. In order to make the decision on one of the coefficients of the fused image, one way is to consider the corresponding coefficients in the source images as illustrated by the red pixels. This is called pixel-based fusion rule. The other way is to consider not only the corresponding coefficients, but also their close neighbors, say a 3x3 or 5x5 windows, as illustrated by the blue and shadowing pixels. This is called window-based fusion rules. This method considered the fact that there usually has high correlation among neighboring pixels. In this research, it has been thought that objects carry the information of interest, each pixel or small neighboring pixels are just one part of an object. Thus, we proposed a region-based fusion scheme. When there is a need to make the decision on each coefficient, it consider not only the corresponding coefficients and their closing neighborhood, but also the regions the coefficients are in. It is observe that the regions represent the objects of interest.

5. Experimental Results

This section demonstrate some experimental results of the proposed method.The results are compared on the basis of the RMSE, for different type of images (kids,medical,satellite) image restored using blind deconvolution (N = 20 iterations) .[J,PSF] = deconvblind(I, INITPSF) deconvolves image I using the maximum likelihood algorithm, returning both the deblurred image J and a restored point-spread function PSF.. The results of blind deconvolution are as shown in Table 1.

Table1.RMSE of the images restore using blind deconvolution(N=20).

Sr.no	Type of image	Blurred noisy image (rmse)	Blind deconvolution for N=20 (rmsek)
1.	Medical	69.9514	77.1854
2.	Kids	45.8178	47.7941
3.	Satellite	46.7137	47.8174

The Results of the second experiment of Wavelet based Fusion are shown in Table 2 (Fused image_1) and Table 3(Fusedimage_2), Table 4 (Fused image_3).where Fused image_1 is the image fusion using DWT by pixel averaging method. Fused image_2 is the image fusion using DWT by maximum likelihood method. Fused image_3 is the image fusion using DWT by window based method.

Table 2 RMSE of the images fusion using averaging pixel method

Sr.no	Type of image	Blurred noisy image (rmse blur)	Image fusion using DWT (rmsek)
1.	Medical	39.4644	62.4161
2.	Kids	26.8725	32.4585
3.	Satellite	38.1441	39.0473

Table 3 RMSE of the images fusion using maximum likelihood method .

Sr.no	Type of image	Blurred noisy image (rmse blur)	Image fusion using DWT (rmsek)
1.	Medical	39.4644	78.8207
2.	Kids	26.8725	51.4416
3.	Satellite	38.1441	50.8605

Table 4 RMSE of the images fusion using window based method .

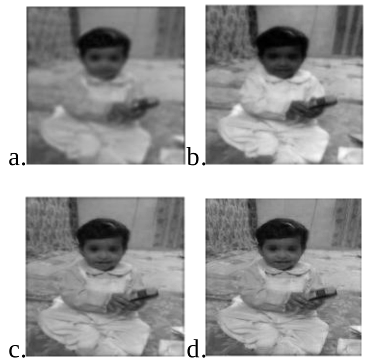


Figure 16.a) kid image a)image fusion using deconvolution. b)image fusion using pixel averaging method. c)image fusion using maximum likelihood method.d)image fusion using window based method

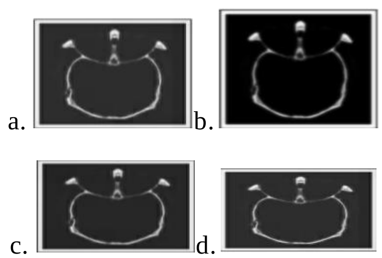


Figure 17 medical image a) image fusion using deconvolution.b)image fusion using pixel averaging method.c)image fusion using maximum likelihood method.d)image fusion using window based method

Sr.no	Type of image	Blurred noisy image (rmse blur)	Image fusion using DWT (rmsek)
1.	Medical	39.4644	30.3697
2.	Kids	26.8725	23.6879
3.	Satellite	38.5179	39.8529

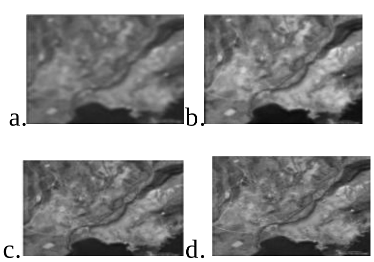


Figure 18. satellite image a) image fusion using deconvolution.b)image fusion using pixel averaging method.c)image fusion using maximum likelihood method.d)image fusion using window based method

6. Conclusion

This research proposes a method to remove the motion blur present in the image taken from any cameras. The blurred image is restored using Blind de-convolution method with N=20 number of iteration and DWT using averaging, maximum likelihood and window based method. The result based on deconvolution does not improve the image quality drastically. If we compare the rmse of blurred image and fused image we can see that fused image rmse is higher than blurred image rmse. It is also proved by performing visual comparison among all the fused image. There is still significant difference between blurred image and fused image of fusion using pixel average and maximum likelihood approach. Medical image rmse is significantly higher than blurred image in all the methods except window based method. The primitive fusion schemes like pixel averaging and maximum pixel perform the fusion right on the source images. These methods often have serious side effects such as reducing the contrast of the image as a whole. But these methods do prove good for certain particular cases wherein the input images have an overall high brightness and high contrast. Further window based method compared for fusion, and it gave the best results. If computationally it's performance is compared it's rmse of fused image for all type of image is minimum, also the fused image quality is improved because the fused image rmse is lower than blurred image rmse. We can do further satisfaction by visual comparison of all the fused images. The challenge is to design a method that exhibits the most appropriate compromise among computational complexity, reliability, robustness to noise, and portability for a given application.

7. References

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