Evaluation of Fusion and Denoising Algorithm for Multifocus Images

Milindkumar V. Sarode, Prashant R. Deshmukh

Abstract—**In this paper, fusion and denoising algorithm for more than two multifocus images is presented. For denoising of more than two multifocus images, concept of minimizing weighted energy function is adapted. For fusion of multifocus images some weighted function are calculated and used. In pixel domain denoising is carried out by using total variation method.**

***Index Terms*—Degradation, Denoising, Fusion, Multifocus, Total Variation.**

I. INTRODUCTION

Denoising of images using fusion approach is an important issue in digital image processing due to the availability of multisensor data in various fields. It is not possible to acquire an image which contains relevant objects "in focus" due to inadequate strength of focus of optical lenses used in charged coupled devices. During acquisition process of images, only the objects "in focus" are clear. Several images can be acquise with various focuses. During the acquisition, images may be degraded. Image fusion technique restores these degraded images acquised with various focuses using camera. Combining several images with different focuses into one uniformly focused image is referred to as the multifocus image fusion [1]. Brief overview of various methods for multifocus image fusion is given in [2]. In practice, images are generally degraded during image acquisition or transmission process. Wavelet methods [5],[6], Variational methods [3],[4] are popular in image restoration. Using the concept of Variational method [1], we presented and evaluated this fusion and denoising technique in pixel domain.

This paper is organized as follows. Section II gives Variational model in spatial domain, Section III gives Design and implementation of suggested approach for fusion and denoising. Experimental results and performance evaluation are shown in section IV, followed by a conclusion and references.

Manuscript received February 3, 2011. This work is supported in part for the research work related to noise reduction in image denoising.

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II. VARIATIONAL MODEL IN PIXEL DOMAIN

In general, images denoising approaches fall into two broad categories: Spatial domain method and Frequency domain methods. Here we used spatial domain method referred to as pixel domain method for image fusion and denoising. The term spatial domain refers to the image plane itself and approaches in this category are based on direct manipulation of pixels in an image.

We are considered three noisy multifocus images $u_1(x)$, $u_2(x)$ and $u_3(x)$ of a picture, where $x=[x_1, x_2]^T \in \Omega$ R^2 and $\partial\Omega$ is the boundary of open Ω [1]. $u_1(x)$ is near focused image, $u_2(x)$ is middle focused image and $u_3(x)$ is far focused images. Here we combined these three multifocused images to form one uniformly focused image u(x), in which objects in the picture are clear and noise is considerably reduced. Based on the variational model for image denoising [1],[4],[8],[9], we propose a variational model for fusion and denoising of more than two multifocused images as follows.

$$w_1 = \arg\min \varepsilon \quad BV(\Omega)\Big\{ E(u) \cong \iint_{\Omega} [w1(x)(u(x)-u1(x))^2 + w2(x)(u(x)$$
$$-u2(x))^2 + w3(x)(u(x)-u3(x))^2\, dx + 3\lambda \iint_{\Omega} |\nabla u(x)|\, dx\Big\} \quad (1)$$

Where BV is the bounded variation space, where images are observed as functions. w1(x), w2(x) and w3(x) are three positive functions, which satisfy $w1(x)+w2(x)+w3(x)=1$, $\nabla u(x)$ is the gradient operator. $\iint_{\Omega} |\nabla u(x)| dx$ symbolize the total variance (TV) of the image u(x). When source images are noise free, second and third terms in (1) disappear. The solution of this model is the pixel-wise weighted average of three multifocus images. We modified a Euler-Lagrange equation to solve variational problem in image restoration described in [1].

$$w1(x)(u(x)-u1(x)) + w2(x)(u(x)-u2(x)) +$$
$$w3(x)(u(x)-u3(x)) - \lambda\, div\left(\frac{\nabla u(x)}{|\nabla u(x)|}\right) = 0 \qquad (2)$$

Time variable "t" is introduced in (2) as;

$$\frac{\partial u(x:t)}{\partial t} = w1(x)(u1(x)-u(x:t)) + w2(x)(u2(x)-u(x:t)) +$$
$$w3(x)(u3(x)-y(x:t)) + \lambda\, div\left(\frac{\nabla u(x:t)}{|\nabla u(x:t)|}\right) \qquad (3)$$

Using time forward difference scheme, solution of (3) is as below.

ISBN: 978-988-19251-4-5
ISSN: 2078-0958 (Print); ISSN: 2078-0966 (Online)

$$u^{(n+1)} = u^{(n)} + \Delta t\left[w1(u1-u^n) + w2(u2-u^n) + w3(u3-u^n)\right] + \lambda div\left(\frac{\nabla u^n}{\left|\nabla u^n\right|}\right) \quad (4)$$

The excellence of image fusion depends on weight function. Edge and structure details in multifocus images blurs due to erroneous fusing of camera. Blurring reduces the modulus of the gradients in the inaccurate focusing regions. To determine weight functions we used gradient based criteria[1], [10],[13].

$$w1(x) = \begin{cases} 1 & if \left|\hat{\nabla} u1(x)\right| > \left|\hat{\nabla} u2(x)\right| > \left|\hat{\nabla} u3(x)\right| \\ 0.5 & if \left|\hat{\nabla} u1(x)\right| = \left|\hat{\nabla} u2(x)\right| = \left|\hat{\nabla} u3(x)\right| \\ 0 & Otherwise \text{ ----------- } \end{cases}$$

$$w2(x) = \begin{cases} 1 & if \left|\hat{\nabla} u2(x)\right| > \left|\hat{\nabla} u3(x)\right| > \left|\hat{\nabla} u1(x)\right| \\ 0.5 & if \left|\hat{\nabla} u2(x)\right| = \left|\hat{\nabla} u3(x)\right| = \left|\hat{\nabla} u1(x)\right| \\ 0 & Otherwise \text{ ----------- } \end{cases}$$

$$\left|\hat{\nabla} u(x)\right| \cong \frac{1}{W}\sum_{z \varepsilon w}\left|\nabla u(x+z)\right|$$

$$w3(x) = 1 - w1(x) - w2(x) \quad (5)$$

Where

$\nabla u(x) = \left[\left(\partial u(x)/\partial x1\right) * \left(\partial u(x)/\partial x2\right) * \left(\partial u(x)/\partial x3\right)\right]$

is the gradient of u(x) at x. $\left|\hat{\nabla} u(x)\right|$ is the local average modulus of gradients in window and w is a window centered at zero. A family of weight functions using local average modulus of gradient with power α for three multifocus images is given as;

$$w_1^\alpha(x) \cong \frac{\left|\hat{\nabla} u1(x)\right|^\alpha}{\left|\hat{\nabla} u1(x)\right|^\alpha + \left|\hat{\nabla} u2(x)\right|^\alpha + \left|\hat{\nabla} u3(x)\right|^\alpha}$$

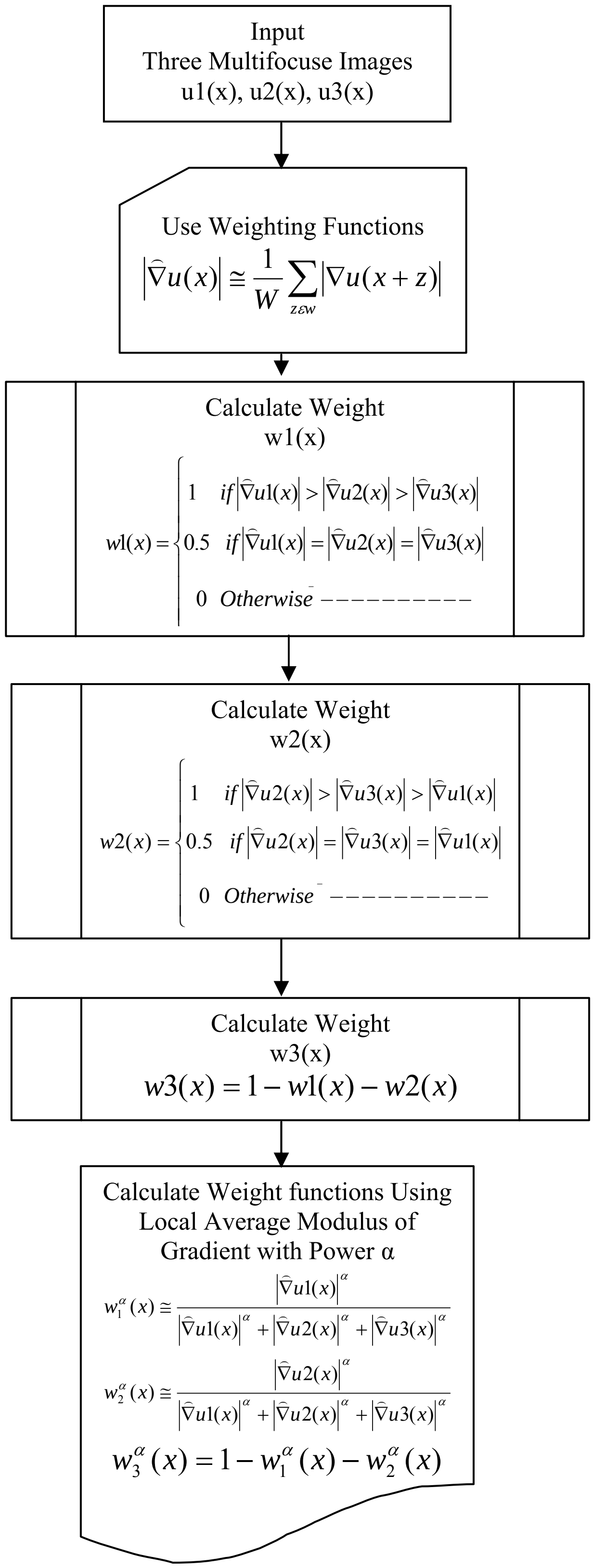
$$w_2^\alpha(x) \cong \frac{\left|\hat{\nabla} u2(x)\right|^\alpha}{\left|\hat{\nabla} u1(x)\right|^\alpha + \left|\hat{\nabla} u2(x)\right|^\alpha + \left|\hat{\nabla} u3(x)\right|^\alpha}$$

and $w_3^\alpha(x) = 1 - w_1^\alpha(x) - w_2^\alpha(x)$, $\alpha \ \varepsilon \ \infty$ (6)

The weight function in (6), generate soft decision maps, which comprehend both image fusion and noise suppression. For edges and textures, the local average modulus of gradients in the correct focused image is often much larger than that in the incorrect focused one [1]. Thus weighted average of (6) gains less degradation of fusion quality as compared with the hard decision maps in (5).

III. Design and Implementation of Variational Model for Fusion and Denoising

Variational model described in section II is designed and implemented in the form of flow diagram. It shows step by step algorithmic solution for the implementation of method. When α → ∞, the weight functions generates soft decision maps, realize image fusion and noise reduction. In smooth region, the values of the weight functions are ≈ 0.5. Since noises in the three images are jointly independent, the average considerably reduces noise in these regions. Flow diagram 1 shows complete algorithmic implementation.



ISBN: 978-988-19251-4-5
ISSN: 2078-0958 (Print); ISSN: 2078-0966 (Online)

IV. Experimental Results and Performance Evaluation

We use three 512 x 512 color images for testing. Figure 1, figure 2, figure 3 and figure 4 shows experimental results. First image is near focused image, where some portion of the image is in "focus" and is clear. While some portion of image out of "focus" and is degraded. Second image is middle focused image in which 50% portion is in "focus" and 50% portion is out of focus and degraded. Similarly third image is far focused. To evaluate the performance of the algorithm visually, we selects clear region in each image. For the quantitative evaluation, we calculate the mean square error (MSE) of a fused and denoised image. Three multifocus images are added by Gaussian noise and Impulse noise and noise levels are measured using standard deviation б. Figure 5 gives performance evaluation of variation method in pixel domain

In this experiment, we consider the variational model in the spatial domain. It is found that, the fusion of the three noisy images using weight function in (6) results in the fact that, noise in the fused image is non stationary. Noise standard deviation for each pixel in the fused noisy image is decided by the weight functions and the noisy standard deviation in the original noisy image in terms of the following rule.

$$\sigma_{\alpha}(x) = \sigma\sqrt{1-3w_1^{\alpha}(x)w_2^{\alpha}(x)w_3^{\alpha}(x)}$$

Above equation shows that, fusion of the three images reduces noise when;

$$w_1^{\alpha}(x)w_2^{\alpha}(x)w_3^{\alpha}(x) \neq 0$$

The noise average standard deviation in the fused noisy image is determined by;

$$\bar{\sigma}_{\alpha} = \frac{\sigma}{\mathrm{N}\times\mathrm{N}}\sum_{\chi}\sqrt{1-3w_1^{\alpha}(x)w_2^{\alpha}(x)w_3^{\alpha}(x)}$$

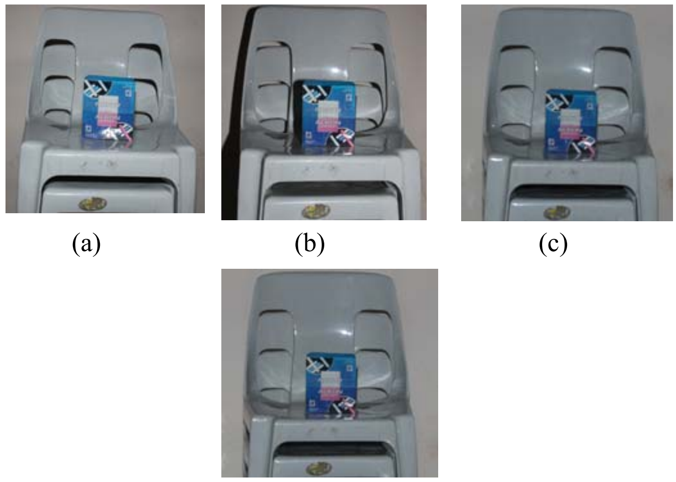
Where, $\mathrm{N}\times\mathrm{N}$ = Number of pixels in images.

To measure the ability of noise reduction, we use the ratio $\bar{\sigma}_{\alpha}/\sigma$. Figure shows graphical evaluation of the method. Table-1 shows the quantitative evaluation of the described method.

(a) (b) (c)

(d)

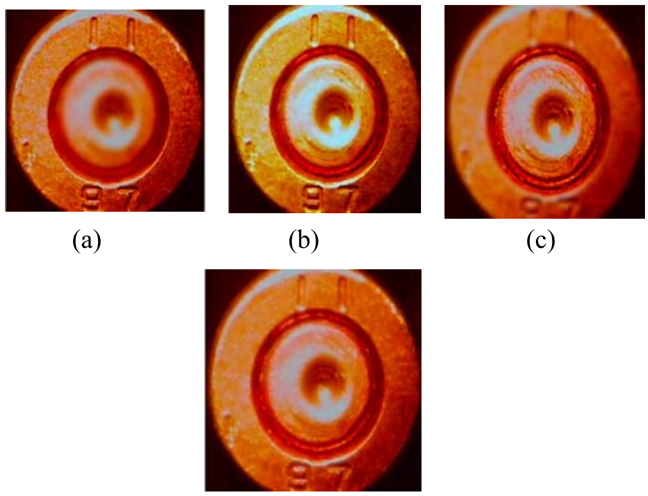
Figure 1. a) Near focused Image, b) Middle Focused Image, c) Far focused image, d) fusion and Denoised Image



(a) (b) (c)

(d)

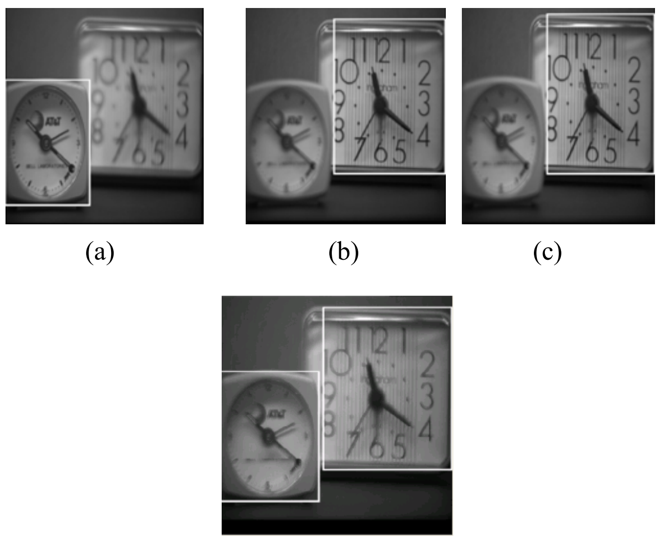
Figure 2. a) Near focused Image, b) Middle Focused Image, c) Far focused image, d) fusion and Denoised Image



(a) (b) (c)

(d)

Figure 3. a) Near focused Image, b) Middle Focused Image, c) Far focused image, d) fusion and Denoised Image



(a) (b) (c)

(d)

Figure 4. a) Near focused Image, b) Middle Focused Image, c) Far focused image, d) fusion and Denoised Image

ISBN: 978-988-19251-4-5
ISSN: 2078-0958 (Print); ISSN: 2078-0966 (Online)

Noise Level	α	Mean Squared Error (MSE)
5	3	≈ 51
10	10	≈ 50
15	14	≈ 50
20	18	≈ 52

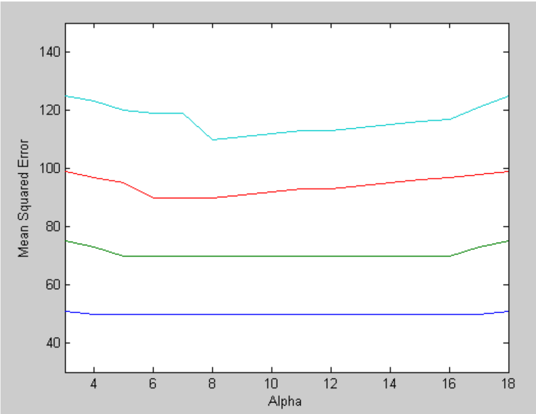


Figure 5. Performance evaluation of the variational method in pixel domain.

V. Applications and Need of Image fusion

Multisensor data fusion has become a discipline to which more and more general formal solutions to a number of application cases are demanded. Several situations in image processing simultaneously require high spatial and high spectral information in a single image. This is important in remote sensing. However, the instruments are not capable of providing such information either by design or because of observational constraints. One possible solution for this is data fusion.

Following are the applications of the image fusion:

1. Image Classification
2. Aerial and Satellite imaging
3. Medical imaging
4. Robot vision
5. Concealed weapon detection
6. Multi-focus image fusion
7. Digital camera application
8. Battle field monitoring

In computer vision, Multisensor Image fusion is the process of combining relevant information from two or more images into a single image. The resulting image will be more informative than any of the input images.

In remote sensing applications, the increasing availability of space borne sensors gives a motivation for different image fusion algorithms.

In satellite imaging, two types of images are available. The panchromatic image acquired by satellites is transmitted with the maximum resolution available and the multispectral data are transmitted with coarser resolution. This will be usually, two or four times lower. At the receiver station, the panchromatic image is merged with the multispectral data to convey more information.

Image fusion has become a common term used within medical diagnostics and treatment. The term is used when multiple patient images are registered and overlaid or merged to provide additional information. For accurate diagnoses, radiologists must integrate information from multiple image formats. Fused, anatomically-consistent images are especially beneficial in diagnosing and treating cancer.

VI. Conclusion

Fusion and denoising model of more than two multifocus images are described in this paper. The experimental results show that the performance of the algorithm is better for the suppression of noise in images.

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