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Performance Analysis of Non Local Means Algorithm for Denoising of Digital Images

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Abstract— Digital images play an important role both in daily life applications such as satellite television, magnetic resonance imaging, computer tomography as well as in areas of research and technology such as geographical information systems and astronomy. Digital image processing remains a challenging domain of programming. All digital images contain some degree of noise. Often times this noise is introduced by the camera when a picture is taken. Image denoising algorithms attempt to remove this noise from the image. In this paper the method for image denoising based on the nonlocal means (NL-means) algorithm has been implemented and results have been developed using Matlab coding. The algorithm, called nonlocal means (NLM), uses concept of Self-Similarity. The image that is taken from the internet has got aligned pixel than the image taken from digital media. Experimental results are given to demonstrate the superior denoising performance of the NL-means denoising technique over various image denoising methods.

Keywords— Noise, Image denoising, Non-Local Means (NL-means) Algorithm, VHDL.

I. INTRODUCTION

Over a few years, the digital images have invaded our everyday life. Numerical cameras make it possible to directly acquire and handle images and film. Their quality is now equivalent to and often higher than for images obtained through photochemical processes. Digital images are much easier to transmit, improve on, and store on data- processing supports.

The need for efficient image restoration methods has grown with the massive production of digital images and movies of all kinds, often taken in poor conditions. No matter how good cameras are, an image improvement is always desirable to extend their range of action.

A. Digital Images

It should be recalled that a digital image is presented in the form of a rectangle divided into small squares or pixels. In the case of a movie, this rectangle has three dimensions, the third one corresponding to time. Each pixel (for picture element) usually contains three numbers ranging from 0 to 255 indicating the amount of red, green and blue (see Figure 1). An adequate combination of these three numbers makes it possible to reproduce any color on a computer screen. In the case of grey-level images, each pixel contains a single value representing the brightness. For the sake of simplicity in notation and display of experiments, we shall usually be content with rectangular 2D grey-level images. All of what we shall say applies identically to movies, three-dimensional (3D) images, and color or multispectral images.

B. Image Processing

Image processing involves changing the nature of an image in order to either

1. Improve its pictorial information for human interpretation.
2. Render it more suitable for autonomous machine perception.

It is necessary to realize that these two aspects represent two separate but equally important aspects of image processing. A procedure which satisfies condition

1. A procedure which makes an image "look better" may be the very worst procedure for satisfying condition.
2. Humans like their images to be sharp, clear and detailed but machines prefer their images to be simple and uncluttered.

Image denoising is one of the most important concepts in computer vision. It is widely used in various image related applications, MRI analysis, 3-D object detection etc. Most digital images contain some degree of noise. The goal of image denoising is to to restore the details of an image by removing unwanted noise. Theoretically, the denoised image should not contain any form of noise.

Over the years, many denoisng approaches have been proposed. Some of the major denosing methods include Gaussian filtering and Wiener filtering etc. However, most of these methods tend to lose fine detail of the image which leads to blurring. In this paper, a non-local means approach is presented, which performs image denoisng while preserving most of the fine detail of the noisy image

Previous methods attempt to separate the image into the smooth part (true image) and the oscillatory part (noise) by removing the higher frequencies from the lower frequencies. However, not all images are smooth. Images can contain fine details and structures which have high frequencies. When the high frequencies are removed, the high frequency content of the true image will be removed along with the high frequency noise because the methods cannot tell the difference between the noise and true image [1][2].This will result in a loss of fine detail in the denoised image. Also, nothing is done to remove the low frequency noise from the image. Low frequency noise will remain in the image even after denoising.

Numerous and diverse denoising methods have already been proposed in the past decades, just to name a few algorithms: total variation[15], bilateral filter or kernel regression[2][16] and wavelet-based techniques.[3][10][19][20]. All of these methods estimate the denoised pixel value based on the information provided in a surrounding local limited window. Unlike these local denoising methods, non-local methods estimate the noisy pixel is replaced based on the information of the whole image. Because of this loss of detail Baudes et al. have developed the non-local means algorithm [1][2][3].

The rest of this paper is organized as follow. In section 2, we introduced the non-local means algorithm. Section 3 provides experimental work and simulation and section 4 provides results and some discussion about above mentioned non-local means algorithm. The last section conclude the whole paper.

C. Related Work

A comprehensive review of the literature on image restoration and denoising is beyond the scope of this paper. I only give a brief summary of the closest related work. One approach to image restoration arises from the variational formulation and the related partial differential equations (PDEs). The Mumford-Shah [1] and the Rudin-Osher-Fatemi total variation [3] models are the pioneering works in variational formulations in image processing. The PDE based approaches [2], [11], [12] are closely tied to the variational formulations. For instance, Nordstrom shows that the popular Perona and Malik anisotropic diffusion PDE [2] is the first variation of an energy[13]. Traditionally, variational formulations have modeled images as piecewise smooth or piecewise constant functions.

While such models are reasonable for some types of images such as certain medical images and photographs of man-made objects, they are too restrictive for other types of images such as textures and natural scenes. To overcome this drawback, variational formulations related to the NLM algorithm that can preserve texture patterns have been proposed [14], [15]. Wavelet denoising methods [16], [17], [18], [19], [20] have also been proven to be very suitable for image restoration. In these approaches, the wavelet transform coefficients are modeled rather than the intensities of the image. By treating wavelet coefficients as random variables and modeling their probability density functions, image restoration can be set up as a problem of estimating the true wavelet coefficients. Patch based approaches can be seen as related to wavelet based approaches when patches are considered as dictionaries [25]. B. Image Neighborhood Based Filtering Buades et al. introduced the NLM image denoising algorithm which averages pixel intensities weighted by the similarity of image neighborhoods [5]. Image neighborhoods are typically defined as 5_5, 7_7 or 9_9 square patches of pixels which can be seen as 25, 49 or 81 dimensional feature vectors, respectively. Then, the similarity of any two image neighborhoods is computed using an isotropic Gaussian kernel in this high-dimensional space.

II. METHODOLOGY

A Whenever an image is processed or applied for segmentation, there exist a few irregularities in the alignment and parameters of the image. This is mainly due to the noise caused by white Gaussian effect (J. Portilla & V. Strela, 2003). Here a concept of denoising is introduced in order to recover the affected image. The process of recovery of digital image which is affected by noise is called denoising.

Starting from a true, discrete image u, a noisy observation of u at pixel i is defined as $\upsilon(i) = u(i) + n(i)$. Let N_κ and $\mathbf{v}(N_\kappa)$ denote a square neighborhood of fixed size centered around pixel κ and the image neighborhood vector whose elements are the gray level values of υ at N_κ, respectively. Also, S_κ is a square search-window of fixed size centered around pixel κ. Then, the non-local means algorithm (1) defines an estimator for u at pixel i as

$$\hat{u}(i) = \sum_{j \varepsilon S_i} \frac{1}{Z(i)} e^{-\frac{\left|v(N_i)-v(N_j)\right|^2}{h^2}} v(j) \tag{1}$$

$$Z(i) = \sum_{j \varepsilon S_i} e^{-\frac{\left|v(N_i)-v(N_j)\right|^2}{h^2}} \tag{2}$$

Where is a normalizing term and parameter h controls the extent of averaging.

We propose to replace the distances $\left|v(N_i)-v(N_j)\right|^2$ in (1) by distances computed from projections of $v(N)$ onto a lower-dimensional subspace determined by PCA. Let M be the number of pixels in the image neighborhood N. Also, let

$\{b_p\}_{p=1}^{M}$ be the eigenvectors of the $M \times M$ empirical covariance matrix for the set of all image neighborhood vectors $\{v(N_j)\}_{j=1}^{Q}$ where Q denotes the total number of pixels in the image. Furthermore, the eigenvectors are sorted in descending order according to their respective eigen values. Then, the projections of the image neighborhood vectors onto the *d*-dimensional PCA subspace is

$$V[d](N_i) = \sum_{p=1}^{d} \langle V(N_i), b_p \rangle b_p / f_p(N_i) \quad (3)$$

where $f_p(N_i)$ is the length of *i'th* vector's projection onto the *p*'th basis vector. Due to the orthonormality of the basis

$$\| V[d](N_i) - V[d](N_j) \|^2 = \sum_{p=1}^{d} (f_p(N_i) - f_p(N_j))^2 \quad (4)$$

Finally, we define a new family of estimators for $d \in (1, M)$

$$\hat{u}[d](i) = \sum_{j \varepsilon S_i} \frac{1}{Z_d(i)} e^{-\frac{\sum_{p=1}^{d} (f_p(N_i) - f_p(N_j))^2}{h^2}} v(j) \quad (5)$$

Where

$$Z_d(i) = \sum_{j \varepsilon S_i} e^{-\sum_{p=1}^{d} (f_p(N_i) - f_p(N_j))^2 h^2} \quad (6)$$

is the new normalizing term. Note that $v[M](N_i) = v(N_i)$; therefore, the proposed approach with $d = M$ is equivalent to the standard non-local means, i.e. $\hat{u}[M](i) = \hat{u}(i)$.

A. Non-local Means Method

Each pixel *p* of the non-local means denoised image is computed with the following formula:

$$NL(V)(p) = \sum_{q \varepsilon V} w(p,q) V(q) \quad (7)$$

where *V* is the noisy image, and weights *w(p,q)* meet the following conditions $0 \leq w(p, q) \leq 1$ and $\sum_q w(p,q) = 1$. Each pixel is a weighted average of all the pixels in the image.

The weights are based on the similarity between the neighborhoods of pixels *p* and *q* [1, 2]. For example, in Figure1 above the weight *w(p,q1)* is much greater than *w(p,q2)* because pixels *p* and *q1* have similar neighborhoods and pixels *p* and *q2* do not have similar neighborhoods. In order to compute the similarity, a neighborhood must be defined. Let N_i be the square neighborhood centred about pixel *i* with a user-defined radius *Rsim*. To compute the similarity between two neighborhoods take the weighted sum of squares difference between the two neighborhoods or as a formula

$$d(p,q) = \| V(N^p) - V(N^q) \|_{2,F}^{2} \quad [1, 2]. \quad (8)$$

Here F is the neighbourhood filter applied to the squared difference of the neighborhoods and will be further discussed later in this section. The weights can then be computed using the following formula:

$$w(p,q) = \frac{1}{Z(p)} e^{\frac{-d(p,q)}{h}} \quad (9)$$

Z(p) is the normalizing constant defined as

$$Z(p) = \sum_q e^{\frac{-d(p,q)}{h}} \quad [1,2] \quad (10)$$

h is the weight-decay control parameter.

As previously mentioned, *F* is the neighborhood filter with radius *Rsim*. The weights of *F* are computed by the following formula:

$$\frac{1}{R_{sim}} \sum_{i=m}^{R_{sim}} 1/(2 \neq i \mid \mathbf{1})^2 \quad (11)$$

where *m* is the distance the weight is from the center of the filter. The filter gives more weight to pixels near the center of the neighborhood, and less weight to pixels near the edge of the neighborhood. The center weight of *F* has the same weight as the pixels with a distance of one [7]. Despite the filter's unique shape, the weights of filter *F* do sum up to one.

Equation (1) from above does have a special case when $q = p$. This is because the weight $w(p, p)$ can be much greater than the weights from every other pixel in the image. By definition this makes sense because every neighborhood is similar to itself. To prevent pixel p from over-weighing itself let $w(p, p)$ be equal to the maximum weight of the other pixels, or in more mathematical terms

$$w(p, p) = max\ w(p, q) \mid p \neq q \mid \tag{12}$$

III. EXPERIMENTAL WORK AND SIMULATION

In this section , to verify the characteristics and performance of non-local means algorithm, a variety of simulation are carried out on the 512*512 bit gray scale image(flower.png & fish.jpg) as shown in fig. 1. All simulations are performed in MATLAB 7.0.[6][7].

In the simulations, firstly images is corrupted by noise and then it is denoised using Non-Local Means Algorithm. Fig. 1 showed conversion of RGB image into gray scale image.

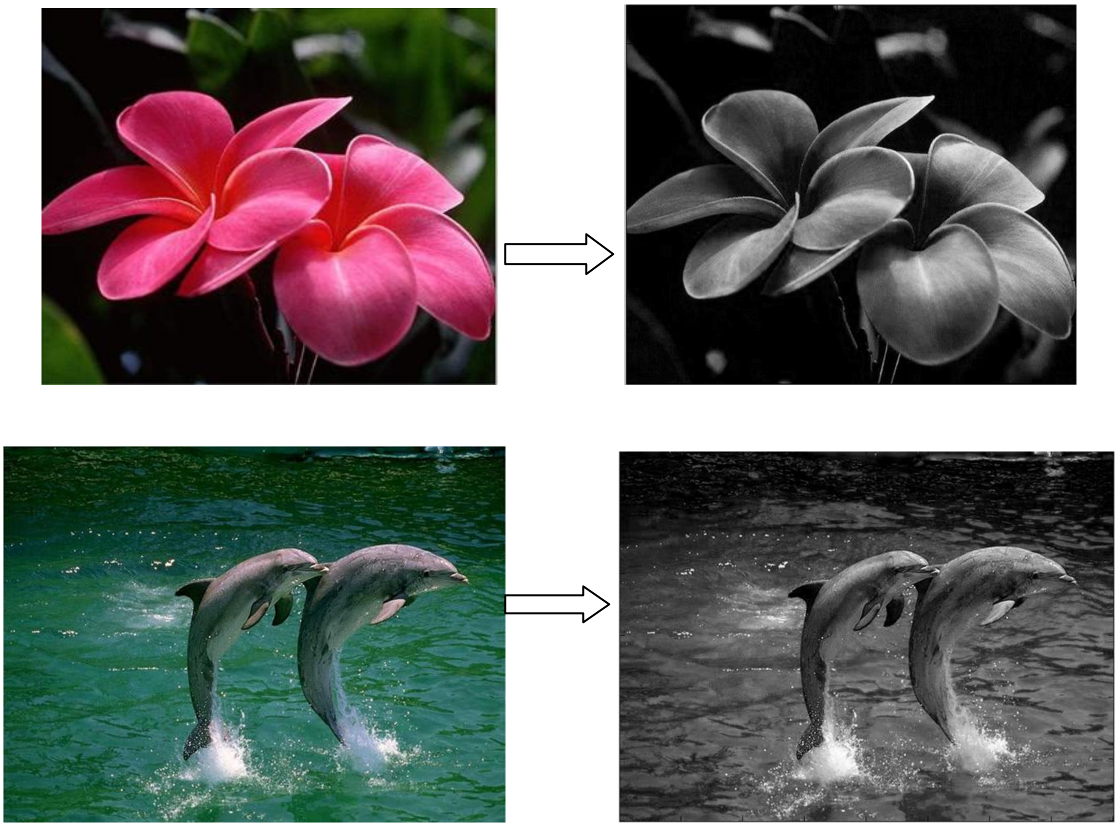

Fig. 1 Conversion of RGB image to Gray Scale Image

Fig. 2 represents adding of Salt and Pepper noise with grey scale image of flower and fish.

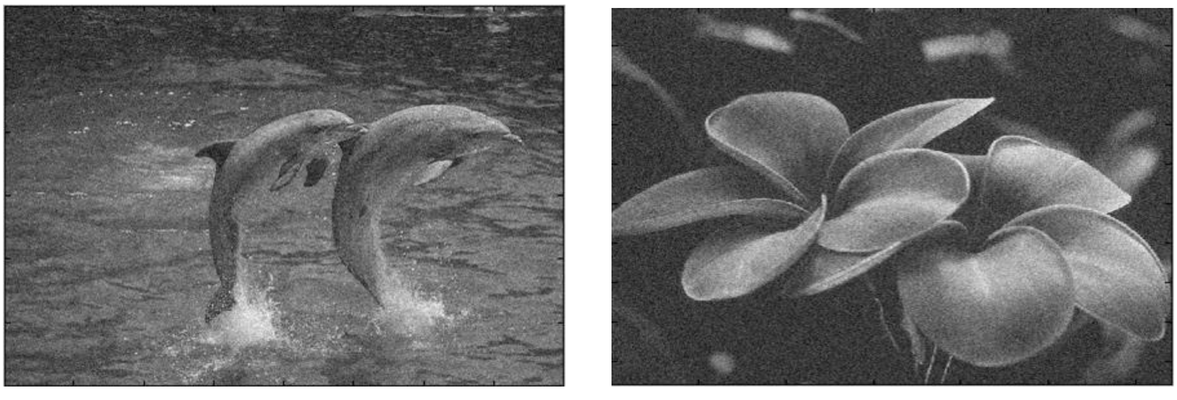

Fig. 2 Grey scale images corrupted by Salt & Pepper noise

The aim of fig. 3 is to compare the quality of denoised image obtained by various denoising method by visual inspection and their histogram representation for flower and fish.

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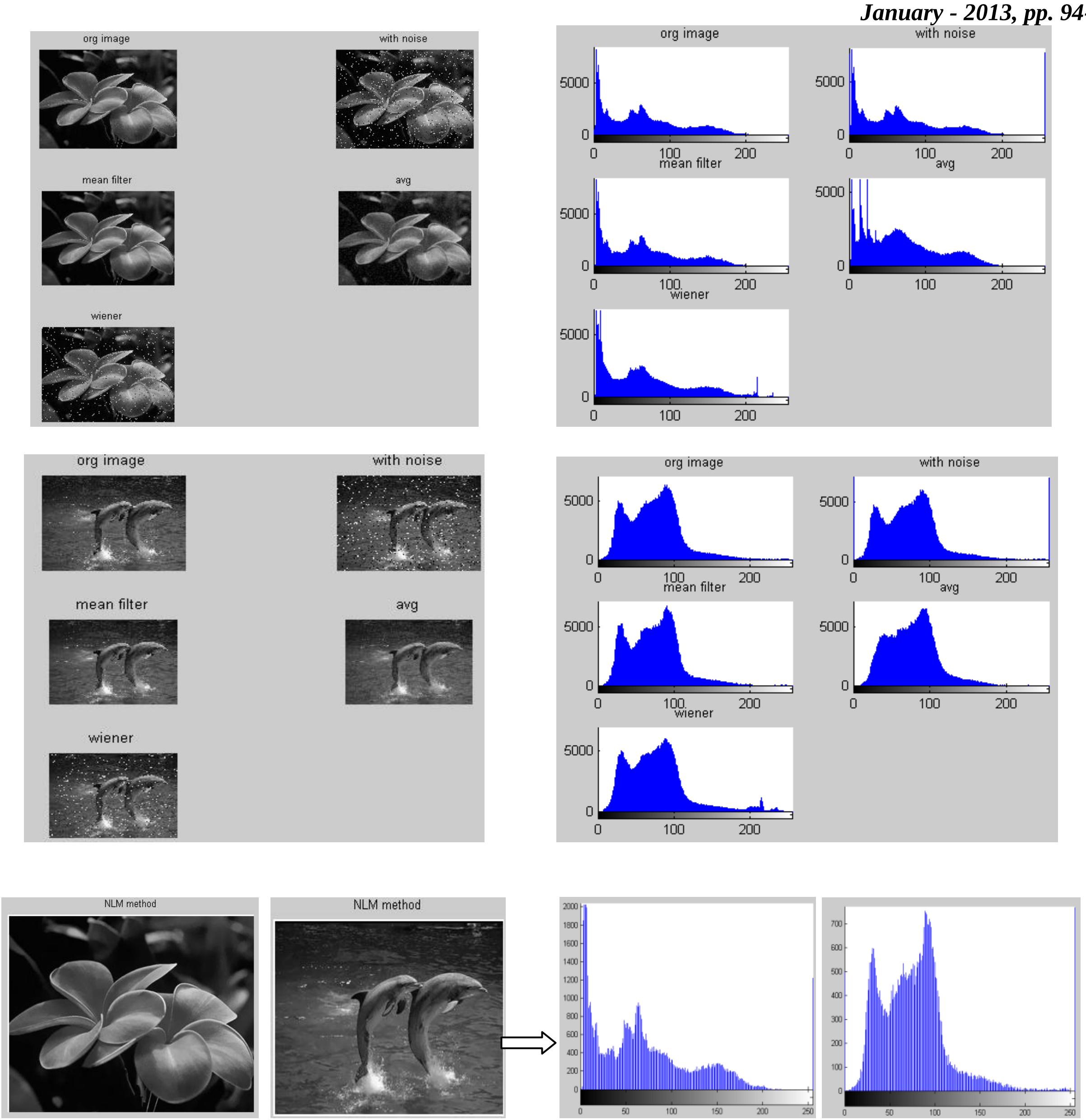

Fig. 3 Original, noisy, mean filter, avg , wiener filter and NLM method image of Flower and Fish and their histogram representation

Mean, Wiener and Average filtering methods were compared to the non-local means method using four different criteria. 1) Visual quality comparison, 2) mean square error (MSE) comparison, 3) Peak Signal to Noise Ratio comparison and, 4) Noise to Signal ratio (NSR) . When compared visually, the denoised images obtained using the non-local means method were clear and did not seem to contain any noise. The MSE of these images were significantly lower.

Table I shows that NLM provides minimum error compare to the other estimate which indicates that NLM is more efficient than remaining methods for image denoising.

Table 2 provides statistical measurement in terms of Peak Signal to Noise Ratio (PSNR) and Noise to Signal ratio (NSR) for digital image of Flower and Fish.

TABLE I

MEAN SQUARE ERROR TABLE

Image	Noisy Image	Mean Filter	Weiner Filter	Average Filter	NLM
Flower	98.0404	22.3681	45.7773	43.3815	38.5673
Fish	99.1193	43.7966	80.5336	69.7614	58.3484

A smaller mean square error indicates that the estimate is closer to the original image.

TABLE 2
COMPARISON CHART

Statistical measurement		**Noisy Image**	**Mean Filter**	**Weiner Filter**	**Average Filter**	**NLM**
PSNR	Flower	8.3027	21.1382	14.9178	15.3847	36.3601
	Fish	15.8769	15.3683	11.3725	10.0950	34.1619
NSR	Flower	0.9838	0.9827	0.8624	0.9552	0.9205
	Fish	0.9747	0.9737	0.9721	0.9741	0.9728

IV. RESULTS AND DISCUSSIONS

There are several transforms that do image denoising. In this paper non local means (NL-means) algorithm [5][6][7] is used. The denoised images obtained with various algorithms are shown in Fig. 5 for visual comparison. Pixel based processing is easy to perform as well as it will give accurate results in comparison to other methods. Two images have been taken in which one is available on system and the other which is taken from the digital media and then downloaded to the computer. Difference is occurred in the processing of two images i.e the image which is already available has got aligned pixels than the image that is downloaded from the digital media.

V. CONCLUSIONS

This paper gives a generalized method for image denoising. Then in depth talk about the non-local means algorithm[7] for removing noise from digital image was given. The based on simulation results, obtained by Matlab 7.0. Non-local means algorithm for image denoising is analyzed on Flower and Fish images. After the analysis of the test results the non-local means algorithm proved to be a better algorithm for image denosing, than its predecessors in terms of the PSNR, MSE and NSR value.

In future the matlab code can be converted to VHDL code and implemented on FPGA kit in order to develop ASIC (application specific IC) for image transformation and analysis. ASIC can be made for doing the specific work of image denoising ,so a person who don’t know any algorithm for image denoising are also capable of doing it.

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