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Implementation of NLM for Denoising of MRI Images by Using FPGA Mechanism

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ABSTRACT: This work provides an insight into the design of an efficient denoising architecture for removal of impulse noise in images. Images are often corrupted by impulse noise in the procedures of image acquisition and transmission. In this work an efficient denoising scheme and its VLSI architecture for the removal of random-valued impulse noise is proposed. To achieve the goal of low cost, a low complexity VLSI architecture is proposed. Here a decision-tree-based impulse noise detector to detect the noisy pixels, and an edge-preserving filter to reconstruct the intensity values of noisy pixels are used. Furthermore, histogram equalization is used to enhance the effects of removal of impulse noise. Our extensive experimental results demonstrate that the proposed technique can obtain better performances in terms of both quantitative evaluation and visual quality than the previous lower complexity methods. Moreover, the performance can be comparable to the higher complexity methods. Its hardware cost is low and suitable to be applied to many real-time applications. These are implemented using Verilog Hardware Description Language. The Verilog code is synthesized on Spartan 3 FPGA using Xilinx ISE 14.7 software tool.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. This Magnetic resonance imaging (MRI) is a medical imaging technique used in radiology to investigate the anatomy and physiology of the body in both health and disease. Denoising of MRI is used to remove noise present in the image. There are several types of denoising methods.Anisotropic Diffusion filtering (ADF) and Non-Local mean filtering (NLM) are few types of denoising methods among them. These filters are used to remove the noise present in images by preserving its edges. By implementing these filters in VERILOG and comparing its result with the help of quality metric such as PSNR, MSE; it is observed that NLM filter has better result than ADF filter, but it has some drawbacks. As the process is computationally intensive, it is a time consuming if implemented in sequential manner. By converting the process in to parallel task, time for computation can be reduced. FPGA is the best option for the same.

KEYWORDS: ADF, Non- Local Mean Algorithm, VERILOG, Field Programming-Gate Array, Verilog.

I. INTRODUCTION

Image processing is widely used in many fields, such as medical imaging, scanning techniques, printing skills, license platerecognition, face recognition, and so on. In general, images are often corrupted by impulse noise in the procedures of imageacquisition and transmission. The noise may seriously affect the performance of image processing techniques. Hence, an efficient denoising technique becomes a very important issue in image processing. According to the distribution of noisy pixel values, impulse noise can be classified into two categories: fixed valued impulse noise and random-valued impulse noise. The former is also known as salt-and-pepper noise because the pixel value of a noisy pixel is either minimum or maximum value in gray-scale images. The values of noisy pixels corrupted by random-valued impulse noise are uniformly distributed in the range of [0, 255] for gray-scale images. There have been many methods for removing salt and-pepper noise, and some of them perform very well. The random-valued impulse noise is more difficult to handle due to the random distribution of noisy pixel values. Here we only focus on removing the random-valued impulse noise from the corrupted image in this paper. Recently, many image denoising methods have

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been proposed to carry out impulse noise suppression. Some of them employ the standard median filter or its modifications. However, these approaches might blur the image since both noisy and noise-free pixels are modified. To avoid the damage on noise-free pixels, an efficient switching strategy has been proposed in the literature.

In general, the switching median filter consists of two steps: 1) impulse detection and 2) noise filtering. It locates the noisy pixels with an impulse detector, and then filters them rather than the whole pixels of an image to avoid causing the damage on noise-free pixels. In addition to median filter, there are other methods used to carry out impulse noise. Generally, the denoising methods can be classified into two categories: lower complexity techniques and higher complexity techniques. The complexity of denoising algorithms depends mainly on the local window size, memory buffer, and iteration times. The lower complexity techniques use a fixed-size local window, require a few line buffers, and perform no iterations. Therefore, the computational complexity is low. However, the reconstructed image quality is not good enough. The higher complexity techniques yield visually pleasing images by using high computational complexity arithmetic operations, enlarging local window size adaptively or doing iterations. The higher complexity approaches require long computational time as well as full frame buffer. Digital image are often corrupted by different types of noise, namely, additive white Gaussian noise, impulse noise and mixed (Gaussian and impulse) noise . Noises are added in the image during acquisition by camera sensors and transmission in the
channel. Hence, image de-noising is one of the most common and important image processing operations in image and video processing applications. Today, in many practical real-time applications, the denoising process is included in end-user equipment, so there appears an increasing need of a good lower-complexity denoising technique, which is simple and suitable for low-cost VLSI implementation. Low cost is a very important consideration in purchasing consumer electronic products. To achieve the goal of low cost, less memory and easier computations are indispensable. In this paper, we focus only on the lower complexity denoising techniques because of its simplicity and easy implementation with the VLSI circuit. Although the field of digital image processing is built on a foundation of mathematical and probabilistic formulation human eyes and analysis play a central role in the choice of one technique versus another, and this choice is often made based on subjective and visual judgments. The impulse noise called salt and pepper causes black and white points appears in digital gray scale images, which chaotically scattered along image areaOver 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. Motivation

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.Image denoising is method to remove noise present in use to recover the original image from noisy measurement. These denoising methods are depends on a filtering parameter. This parameter measures the degree of filtering applied to the image. For most methods, the parameter h depends on an estimation of the noise variance $\sigma 2$. The result of a denoising method D_h as a decomposition of any image v as

$$v(i) = u(i) + n(i) \qquad (1)$$

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Where, v(i) is observed value, u(i) is true value and n(i) is noise perturbation at a pixel i. As indicated, the amount of noise is directly prportinal signal-dependent. In noisy model, consider the independent random variables at different pixels the normalized values of n (i) and n (j) [3].

Different types of methods have been proposed to remove the noise and recover the true image u. Even though it may be very different in tools, but it must be emphasized that a wide class shares the same basic remark diagnosing is achieved by averaging. This averaging may be performed locally: the Gaussian smoothing model, the anisotropic filtering and the neighborhood filtering, by the calculus of variations: the Total Variation minimization or in the frequency domain: the empirical Wiener filters and wavelet thresholding methods. The decomposition of any image v is nothing but a denoising method Dh is given by

$$v = D_h v + n(D_h, v) \qquad (2)$$

Where, v is noisy image, h is filtering parameter which depends on the standard deviation of the noise. Originally, v (Noisy Image) is not as smooth as $D_h v$ and in reality a white noise is looks like n(Dh, v). In Y. Meyer studied the suitable functional spaces for this decomposition. The primary scope of this latter study is not denoising since the oscillatory part contains both noise and texture. The denoising methods should not any change in the original image u.

Now, most denoising methods minimize or remove the fine details and texture of u. In order to better understand this removal, he shall introduce and analyze the method noise. The difference between the original image u and its denoising version is called as method noise. Firstly we need to compute and analyze this noise procedure for a wide range of denoising algorithms, namely the local smoothing filters. The non local means (NL-means) algorithm is based on a non local averaging of all pixels in the image and it is defined by the simple formula

$$NL_h[u](x) = \frac{1}{C(x)} \int \int_{\Omega} w(x, y) u(y) dy \qquad (3)$$

Where, $x \in \Omega$ and $C(x) = \int_{\Omega} w(x, y) dy$ is normalizing constant, Ga is a Gaussian kernel and h acts as a filtering parameter. By using this formula the denoise value at x is a mean of the values of all points whose Gaussian neighbourhood looks like the neighbourhood of x.

By using all possible predictions of the image can provide is difference of local filters or frequency domain and NL-means algorithm.

II. RELATED WORK

Many denoising schemes are "decision-based" median filters. This means that the noise candidates are first detected by some rules and are replaced by the median output or its variants. These schemes are good because the uncorrupted pixels will not be modified. However, the replacement methods in these denoising schemes cannot preserve the features of the images, in particular the edges are smeared. a decision based algorithm is proposed. In this, image is denoised by using a 3×3 window. If the processing pixel value is 0 or 255 it is processed or else it is left unchanged. The selected 3× 3 window elements are arranged in either increasing or decreasing order. Then the pixel values 0's and 255's in the image (i.e., the pixel values responsible for the salt and pepper noise) are removed from the image. Then the median value of the remaining pixels is taken. This median value is usedto replace the noisy pixel.[2]In medical image processing, medical images are corrupted by different type of noises. It is very important to obtainprecise images to facilitate accurate observations for the given application. Removing of noise from medical images is now a very challenging issue in the field of medical image processing. Most well known noise reduction methods, which are usually based on the local statistics of a medical image, are not efficient for medical image noise reduction. This paper presents an efficient and simple method for noise reduction from medical images. In the proposed method median filter is modified by adding more features. Experimental results are also compared with the other three image filtering algorithms. The quality of the output images is measured by the statistical quantity measures: peak signalto- noise ratio (PSNR), signal-to-noise ratio (SNR) and root mean square error (RMSE). Experimental results of magnetic resonance (MR) image and ultrasound image demonstrate that the proposed algorithm is comparable to popular image smoothing algorithms. [3]This paper presents a novel method for Bayesian denoising of magnetic resonance (MR) images that bootstrap itself by inferring the prior, i.e., the uncorrupted-image statistics, from the corrupted input data and the knowledge of the Riciannoise model. The proposed method relies on principles from empirical Bayes (EB) estimation. It models the prior in a nonparametric Markov random field (MRF) framework and estimates this prior by optimizing an information-theoretic metric using the expectation-maximization algorithm. The generality and power of nonparametric modeling, coupled with the EB approach for prior estimation, avoids imposing ill-fitting prior models for denoising. The results demonstrate that, unlike typical denoising methods, the proposed method preserves most of

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the important features in brain MR images. Furthermore, this paper presents a novel Bayesian-inference algorithm on MRFs, namely iterated conditional entropy reduction (ICER). This paper also extends the application of the proposed method for denoising diffusion-weighted MR images. Validation results and quantitative comparisons with the state of the art in MR-image denoising clearly depict the advantages of the proposed method. The method generalizes in a straightforward manner to multimodal MR images and vector-valued images. An intrinsic limitation of the nonparametric prior-PDF model is that its performance degrades for image regions not having sufficiently-many repeated patterns. For instance, the proposed method may find it difficult to denoise features/structures that occur rarely in the image because of theoretically-insufficient data to feed into the nonparametric model. [4]It describe approximate digital implementations of two new mathematical transforms, namely, the ridgelet transform and the curvelet transform. These implementations offer exact reconstruction, stability against perturbations, ease of implementation, and low computational complexity. A central tool is Fourier-domain computation of an approximate digital Radon transform. This introduce a very simple interpolation in Fourier space which takes Cartesian samples and yields samples on a rectopolar grid, which is a pseudo-polar sampling set based on a concentric squares geometry. Despite the crudeness of interpolation, the visual performance is surprisingly good. Ridgelet transform applies to the Radon transform a special over complete wavelet pyramid whose wavelets have compact support in the frequency domain. Curvelet transform uses ridgelet transform as a component step, and implements curveletsubbands using a filter bank of wavelet filters. In the tests reported here, simple thresholding of the curvelet coefficients is very competitive with “state of the art” techniques based on wavelets, including thresholding of decimated or undecimated wavelet transforms and also including tree-based Bayesian posterior mean methods.

It was introduced a Gabor function in theory of communication. By using this image enhancement and examine the result with an early proposal method for image deblurring. Deblurring process compares two stages one for estimates the amount of blurring and another stageperforms based on estimate obtained. He was considered only blurring process in which equivalent diffusion time span was known. Deblurringprocess is a directional blurring process. Hence, due to this directional blurring one problem is occurring, Gabor method is the smoothing of the image in only one direction. Itdiscoverd a class of algorithms that realize it was using a diffusion process. The advantages of this methods are it is the simplest version of anisotropic diffusion and can be applied with success to multiscale image segmentation. ADF preserves not only edge junctions but also the speed of computation which is perfect and the drawback is the level of Noise varies significantly, making the system insufficient to obtain a correct multiscale segmentation. Moreover, anisotropic diffusion can reduce the amount of work. It discovered a new algorithm about image restoration that based on mean curvature motion. In this algorithm he explained the most possible among all multiscale image smoothing method and preserving uniqueness and stability. The advantage of this method is it preserving uniqueness and stability.It introduced a scheme for edge preserving smoothing and bilateral filtering. By taking the means of a nonlinear combination its surrounding image value this filter preserves the edges and smoothes images. The combination of gray levels or colours based on both their geometric structure of closeness and their photometric mirrorview and prefers near values to distant values in both domain and range. He implemented by a single layer of neuron-like devices that perform their operation once per image. In bilateral filtering, he not only explained the filtering domain and similarity metrics different from Gaussian but also explained the range filters can be combined with different types of domain filters which includes oriented filters. The disadvantage is that bilateral filters are harder to analyze than domain filters, because of their nonlinear nature.It discussed the total variation of the image is minimized subject to constraints involving the statistics of the noise in Non-linear total variation based noise removal algorithms. This method used the Lagrange multipliers and gradient-projection method and run the two-dimensional algorithm on graphs and real images. It consider the range from 0 to 255 and the Gaussian white noise is added when the resulting values lie outside this range. The purpose to display this range is only for threshold, however the processing takes place on a function whose value generally lie arbitrarily far outside the original image. Itintroduces a reconstruction function which is Soft-Thresholding for an unknown function from noisy data. It was explained in the wavelet domain by translating all the empirical wavelet coefficients toward zero. He proved that two results of this type of estimator, one is smooth and another is adapted. These two properties are unprecedented in several ways. The high probability function is at least as smooth as in any of a wide variety of smoothness measures this happens due to smooth estimator. And the estimator comes nearly as close in mean square to any measurable estimator can come, uniformly over balls in each of two broadscales of smoothness classes this is due Adapt. Stanley Osher et al.[12] explained total variation minimization and the H−1 Norm. A new model is used for image restoration and image decomposition into cartoons and texture, based on the total variation minimization. The advantage of this proposed model was that it performs better on textured images and the decomposition of an image between a smooth part and a non smooth or oscillatory part.

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It proposed a new method in Texture Synthesis by Non-parametric Sampling that explained parametric methods for texture synthesis. Texture synthesis is a process which grows a new image outward from an initial seed. This method of synthesizing uses a pixel when its neighborhood pixels are already known. This method cannot be used for synthesizing the entire texture or even for hole-filling since for any pixel the values of only some of its neighbourhood pixels will be known. The main advantage of this method is to produce good results for a wide variety of synthetic and real-world textures by preserving as much local structure as possible. The future plan of this proposed method was an automatic window size selection, including non-square windows for elongated textures. This algorithm was quite slowly, hence it was time consuming.

III. METHODOLOGY USED

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 $N\kappa$and $v(N\kappa)$ 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 $N\kappa$, respectively. Also, $S\kappa$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

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

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

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

A. Stage I

1) ANISOTROPIC DIFFUSION FILTER

As raw data consist of noise due to that image denoising is necessary to remove it. To remove this noise present in the database and to get the clear image, image denoising is necessary. Consider the basic concept of ADF filter in Perona-Malik we are design it. By taking the MRI image as an input if the image is color to then first convert it into the gray image. From this input image we can find out first the normalized image. By taking this normalized image as a reference, we can compare this image to the output of the filter image until the better image is obtained.

To find out better image than normalized consider some parameter are applied to the magnitude images scaled to a range of [0, 1], number of iterations, integration constant and gradient modulus. For convolution purpose, we are using the 2D convolution mask in this matrix we are considering its central pixel is 1 and its neighbors are represented by -1. This mask is convolved with the difference image to calculate the diffusion coefficient and it can be calculated by two types. To find out better diffusion image, we are considering the output image of diffusion filter as a reference to the next image and so on. This procedure is continued until we get better images than a normalized image. After getting this diffusion image,calculate the PSNR of that diffusion image. The result are shown given below. The output images have good image and we can detect edges easily.

2) NON-LOCAL MEAN ALGORITHM

By considering the basic concept of NLM in A. Buades, it is implemented. Non-local mean algorithm is used in image processing for image denoising. In local mean filters take the mean value of a group of pixels surrounding a target pixel to smooth the image, but non-local means filtering takes a mean of all pixels in the image and calculate the weight of similar pixels which are the target pixel. Due to this the detail in image result in less loss of compared with local mean filter. These filters are implemented in VERILOG and its results. By comparing both filter output parameters then it is found that NLM has better results than ADF. Results are shown in table 1. The advantage of NLM over ADF is that it has better results than ADF, Edge Enhancement as shown in fig 1 and 2. As it reads data sequentially so it is a time

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consuming in VERILOG which is its drawback. To overcome this drawback this filter is implemented in FPGA by using Verilog.

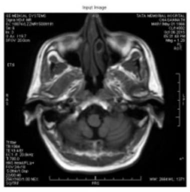
B. **Stage II**

In this method we have to first convert image into .coe file then it gives as an input to FPGA by using block memory in IP core. Give the meory of image to this block memory and load the .coe file. After this we have to calculate the weighted euclidiean distance of targeted pixel after that calculate there weight repeat this procedure upto to tha last pixel after that calculate the final value.

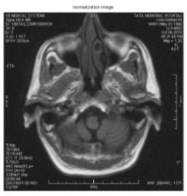
IV. EXPERIMENTAL SETUP

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 VERILOG 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.

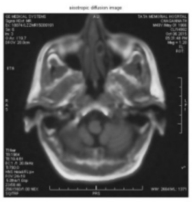
A. **Quantitative results**



(a)



(b)



(c)

Fig. 1. **Anisotropic Diffusion Filter a) Input Image b) Normalized Image c) ADF output**

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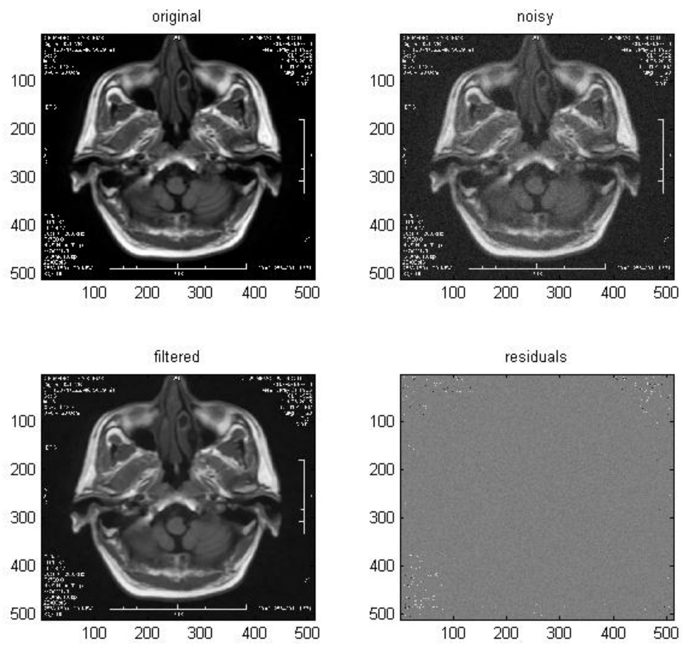

Fig. 2. **Non Local Mean Filter: Input Image, Noisy Image, Filtered Image, Residuals.**

Fig. 3.

B. Qualitative results

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

TABLE II. Output of ADF and NLM with various parameters

PArameter and Filter	PSNR	MSE	SSIM	SNR	CNR
ADF	28.7753	86.2095	0.08186	0.142	41.0514
NLM	29.7128	69.4701	0.9770	0.0904	47.4522

V. 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

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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. 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 VERILOG 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 VERILOG 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.

VI. CONCLUSIONS

A new signal denoising technique was proposed for MRI signals. The new strategy based on spectral subtraction method is adaptive and simple to implement while offering a substantial improvement of the SNR. The implementation was described and its performance was demonstrated using computer simulations and real data. Further work is needed to investigate the potential of the new technique in different clinical applications. The response of the SSD filter depends on the input signal. It is an SNR-dependent filter wherein lower SNR components are attenuated more than higher SNR components, which may introduce subtle image blurring for low-level signals. The SSD method is immune to such effects when the data acquired from each coil element are separately denoised using its measured average noise power spectrum,

which can vary significantly between elements. The present results also suggest that SSD can be applied in situations wherethere is inherent physiological noise and motion such as in the heart. We have shown SNR improvements of up to 45% for MRI using SSD in both single and array coils reconstruction while preserving image details in simulations and, in practice, in phantoms and multichannel brain and cardiac MRI. The SSD method performs comparably to ADF in terms of SNR improvement, and superior to ADF with respect to accuracy and the retention of structural detail, at a reduced computational load. In future, additional to denoising using filters for rician noise and fractional Brownian (Gaussian) noise, deblurringcan be performed for further preservation of image characteristics.

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