A Morphological Filtering based technique for Simultaneous Enhancement and Denoising of Grey Scale Images

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***Abstract*—**Image denoising plays a vital role in pre-acquisition and post acquisition imaging applications. In context to ever growing demand of image denoising we designed an algorithm based on the morphological operations i.e. opening and closing operations. The error images depicting the gradient features and details are calculated to enhance the amount of information in the denoised images. The final results are obtained using median filtering on the eight bit planes. The reconstructed images with denoised bit planes show high quality of visual as well as quantitative results.

Keywords*—opening operation; closing operation; morphology;gaussian filter; median filter*

I. INTRODUCTION

Image denoising is a fundamental problem in image processing that has been widely studied in the past decades. It aims at restoration of a high quality image from its degraded noisy version. Image noise reduction serves as an actual foundation in many applications such as medical imaging, object recognition, surveillance and remote sensing [1].

Image denoising also serves as an important pre-processing step in image fusion and directly affects the image fusion quality [2-6]. An ideal image denoising algorithm is designed to suppress the unwanted noise while preserving as many signal details as possible. The images are often contaminated with noise while acquisition and transmission. The corruption of the images leads to a significant reduction in image quality which makes the high-level vision tasks such as object recognition and scene interpretation extremely difficult. Hence removal of noise is an extremely important step in any kind of image processing application.

Noise can be perceived as a random fluctuation in the colour information or the intensity value of the image pixels. The stochastic nature of photons and the electronic and thermal fluctuations of electrons are the prime sources of noise during image acquisition. The conditions with lower power light source, short exposure time and phototoxity, the source of noise being signal dependant forms another reasonable source of image noise [7].

The major types of image noise being studied in literature are Gaussian Noise, Salt and Pepper Noise, Poisson Noise and Rician Noise. The most common simplifying assumption while solving denoising problems is that the image is corrupted with Gaussian Noise. This is because the Gaussian noise is uniformly distributed and is the prevalent in the highest amount in images. A lot of image denoising techniques have been proposed in the past two decades. These techniques range from the earlier smoothing filter and transform domain methods to more recent ones such as convolution sparse representation based methods and hybrid methods [8].

Image denoising can be exploited three domains namely spatial domain, transform domain and dictionary learning methods. Some of the representative methods of image denoising are Gaussian Filter, Median Filter, Wavelet based soft shrinkage, non-local mean filter, BM3D, BLS-GSM, LPG-PCA, Bilateral filtering, NSST, morphological operations, K-SVD and convolution sparse representation.

The spatial domain methods preserve the low contrast details while compromising on edges and details, whereas the transform domain methods tend to represent the texture details efficiently. However the present day methods exploit the attributes of spatial and transform domain methods [9].

The main goal of an image denoising algorithm is to recover as many feature details as possible from the corrupted image into the reconstructed image. In computer aided tools, the high quality of these restored images is extremely required. The image enhancement techniques play a major role in improving the overall edge information in the images.

Majority of the denoising techniques are able to work well on low noise levels. However in order to smoothen the images, most of the denoising algorithms tends to over blur the edges at high noise levels, hence results in information loss. In this paper we have designed a simultaneous edge enhancement and edge preservation image denoising technique with help of morphological operations and spatial domain filters

II. PROPOSED METHODOLGY

In this section the detailed flow of proposed algorithm is given. The 256×256 grey scale images such as MR (Magnetic

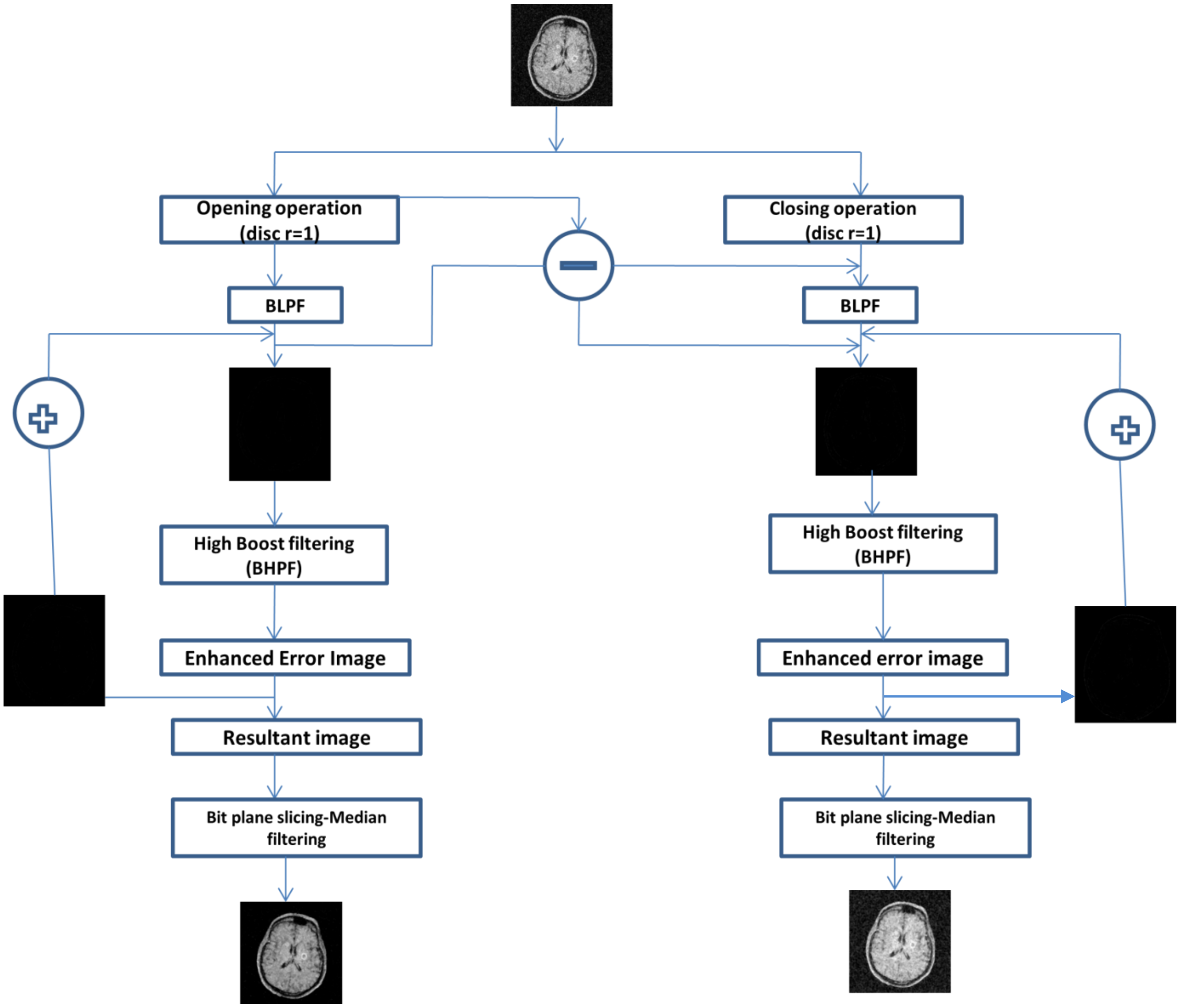

Fig 1. Flow Diagram for the proposed methodology

Resonance) image is taken as input data set to validate the application of the proposed algorithm. The input data said is made noisy at standard deviation 10, 20, 30 and 40. The flow diagram for the proposed methodology is given in Fig.1

A. Detailed Fusion Algorithm

Morphological operations deal with tools to extract image features that are useful in description and representation of a shape. In the given algorithm the morphological operators are applied in order to extract the maxima's (the high contrast edge details) and minima's (the low contrast large objects) from the image. Erosion and dilation are the two basic fundamental functions in mathematical morphology. Dilation and erosion expands and shrinks the components of an image respectively. The erosion process in morphological filtering can be viewed as the structuring out of the details smaller than the structuring element. Erosion thins the object in the binary image whereas dilation thickens or grows the object in an image [10].

The opening operation on a set A of an image can be defined as the dilation of the erosion of A by a structuring element B (which is a disc operator with radius=1 in this case), denoted by $A \odot B$. The closing and opening are dual of each other. Therefore closing of a set A can be given as the erosion of the dilation of A by structuring element B denoted by $A \bullet B$. The opening operation smoothes the counters of an object, breaks narrow edges and removes the ridges, whereas closing generally fuses the narrow dips and eliminates small holes while smoothing the sections of the object counters [10].

In this manuscript the outputs by applying both opening and closing operation on the image are obtained and be denoted by *Ao* and *Ac*.

The opening and closing operation outputs so obtained are further smoothened using Butterworth Low pass filtering (BLPF). BLPF is a low pass filter which removes the noise pixels by the principle of thresholding frequency. The BLPF is employed at order 2 and cut off frequency 50 [10].

Let both the BLP filtered images be denoted by *B(Ao)* and *B(Ac)*. Now the BLPF output for opening operation is subtracted from the output of the closing operation i.e. *Ac−B[Ao](error image I)* and similarly output for the closing operation is subtracted from the output of the opening operation i.e. *Ao−B[Ac](error image II)* to obtain the error images. The error images so obtained in each case depict the edge and detail features which have been eliminated out in the opening and closing operation. These error images are further processed with BHPF [11,12] high boost filtering to induce contrast enhancement in the error image. The BHPF is employed at order 3 and cut off frequency 10. The enhanced error image I recover the feature details which has been eliminated out in the opening operation and enhanced error image II represents the edge details which have been factored out in closing operation. This step is done to obtain the edge strengthening details. The error image I is added to the output of the opening operation resulting in an enhanced image *(IM1)* and error image II is added to the output of the closing operation *(IM2)*.

The resultant IM1 and IM2 are decomposed with bit plane slicing [10]. An 8 bit images is composed of eight one bit planes while lowest bit plane containing the least significant data and highest bit plane composed of the most significant data. Each of bit planes obtained from IM1 and IM2 are subjected to median filtering. Median filtering is an image denoising algorithm designed to remove sharp peaks and preserve edges and details. The denoised bit planes of IM1 and IM2 are combined together to get the resultant denoised images R(IM1) and R(IM2)

The results so obtained are analyzed by computing the PSNR (Peak signal to noise Ratio) values and visual perception.

III. RESULTS AND DISCUSSIONS

To validate the proposed algorithm we have tested it for synthetic i.e. MRI image which is shown in Fig 2(a). The noisy images corrupted with normally distributed Gaussian Noise at standard deviation 10, 20, 30 and 40 are shown in Fig 3. For comparative analysis we have depicted the denoised results with Gaussian filter [10], median filter [13] and wavelet shrinkage with visu soft thresholding [14] (fig 4,5 and 6 respectively). The final denoised images for opening and closing operation are shown in Fig 4 and 5 respectively. The objective evaluation metrics are given in Table 1.

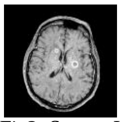

Fig2. Source Image

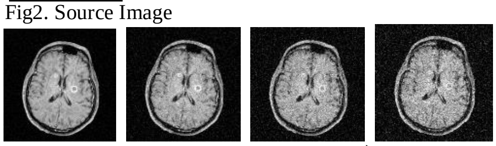

Fig3. Noisy Images at σ=10,20,30,40 (L-R)

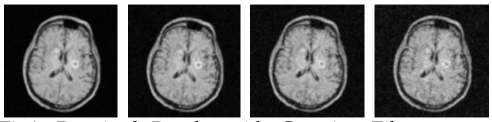

Fig4. Denoised Results with Gaussian Filter at σ=10,20,30,40 (L-R)

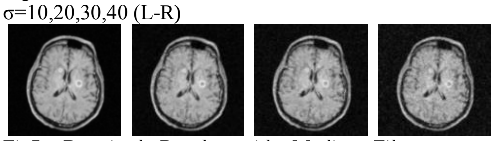

Fig5. Denoised Results with Median Filter at σ=10,20,30,40 (L-R)

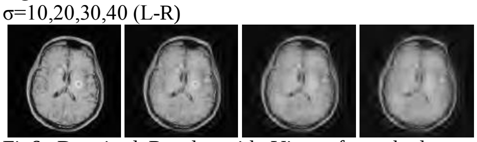

Fig6. Denoised Results with Visu-soft method at σ=10,20,30,40 (L-R)

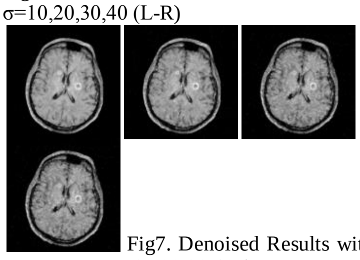

Fig7. Denoised Results with opening operation at σ=10,20,30,40 (L-R)

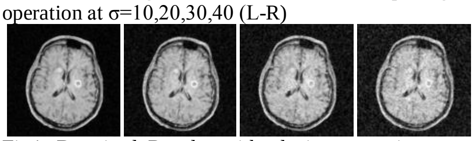

Fig4. Denoised Results with closing operation at σ=10,20,30,40 (L-R)

From the figures shown above it can be seen that as the amount of the noise increases in the images, there is a significant loss in details in image denoising results. It is clearly depicted that the visu-shrink with soft thresholding gives the worst kind of visual results as the intrinsic details and features in the image are totally blurred at higher noise levels. At low noise levels i.e. σ=10 and 20 all the denoising algorithms existing and the proposed ones shows similar performances. As far the subjective assessment is concerned the output images with closing operation shows the best visual quality of results. While comparing the visual results of opening and closing operation, closing gives better quality results as there is increased amount of contrast induction in the final results at noise values.

In objective evaluation from Table 1, the PSNR values are the highest for the opening operations at all standard deviation values of noise. The closing operation outperforms all other existing denoising methods used at

MRI image	*GF*	*MF*	*Vi-soft*	*Proposed (Closing)*	*Proposed (Opening)*
σ=10	26.38	24.35	26.14	26.96	**27.96**
σ=20	25.38	23.74	22.76	23.82	**26.04**
σ=30	24.21	22.96	20.82	21.21	**23.92**
σ=40	22.84	21.98	19.48	19.00	**22.03**

standard deviation 10. Though the PSNR values are highest for opening results, there is a higher amount of contrast induction in closing results. Hence it can be concluded that the proposed methodology gives an efficient way of catering noise in MRI image with considerable amount of PSNR values and good visual quality results.

IV. CONCLUSION

With the employed of morphological operations we have presented a image denoising algorithm which is able to preserve edges and features details with considerable amount of denoising. The results have been given both for opening and closing operations to depict the results with varying contrast levels. The proposed method is able to outperform the various existing image denoising filters. This technique can be further improvised by optimizing it use of various transform domain methods and varying levels of iterations for increased smoothing.

IV. REFERENCES

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