Image Denoising by Curvelet Transform Based Adaptive Gaussian Notch Filter

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Abstract. In this work a new adaptive Gaussian notch filter (AGNF) with curvelet transform is proposed for removing noises from Magnetic Resonance Images. MRI images corrupted by periodic noises which are occurred because of interferences during image capturing. In general, the interferences occur due to electric or magnetic circuits. These periodic noises can be identified by repetitive patterns formed in the image. Since periodic noises affects the image quality the elimination of this noise is very important. The Adaptive Gaussian Notch filter identifies noisy peak areas and eliminates corrupted regions, also size of window is varied based on size of the noisy frequencies of the noise affected frequency domain image. This window size is varied from smaller size to the size of the noisy peak areas. The Curvelet transform having very high degree of directionality and anisotropy compared with Fourier transform and wavelet transform. In which both Fourier transform and curvelet transform were used to isolate noise regions. Finally, the calculated PSNR values were compared and the best one were identified.

Keywords: AGNF, Curvelet, Fourier, PSNR

1 Introduction

In general, magnetic resonance images plays a vital role in the study of brain tissues but they are corrupted because of Rician noise, Gaussian Noise and Rayleigh noise. These noises were generated because of several factors like bad lighting, heat, long exposure time, errors developed in switching circuits and storage and image capturing devices. The MRI noises change the intensity values of actual images [1]. From the noisy image the original image can be recovered with the help of several image restoration techniques. [2, 3].

Radiations and magnetic induction between circuits of electrical sources exhibit periodic structures in MRI. When the electric interferences happened during the image capturing process periodic noises in the form of repetitive structure occurred at various frequencies added with original image where the amplitude of this repetitive structure define the level of noise added with the uncorrupted image [4].

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This periodic noise due to interference developing line drop out, stripes and change of visible from one colour to another which makes problem in the reproduction methods such as half-tone printing [5] and cathode ray techniques [6].

The changes in the pixel values of images produce image noise. They will be generated in many ways. One of such generation is development of periodic noises because of interferences due to electric circuits and mechanical devices along with voltage level variations and temperature changes [7]. Also, if image capturing devices not properly fixed with their holding devices generate periodic noises [8]. Periodic noises having sinusoidal waveform structure with particular time period and repeats that pattern at regular intervals. These periodic noise waveforms will be appeared in the video signals if the strength of the received signal is attenuated due to any factors while the reception of TV signals by TV receivers [9].

While the electronic transmission of images they may be disturbed by some external factors they may degrade the image quality. In X-ray device also this periodic pattern will be appeared in the process of continuous acquisition of images [10, 11].

In the periodic noise affected image the repetitive patterns will be appeared in addition with the original image. In the frequency domain these noises can be appeared as spikes. In the image capturing device of MRI due to radiations and flux linkage between electric circuits produces periodic noises which affect brightness level of images and also induces inter-slice changes [12]. In paintings the repetitive structures formed by contaminations [13].

In general, the frequency domain representation of MRI image can be obtained by Fourier transform which is highly affected by periodic structures due to improper RF coil connections in the image capturing device [14]. Also, MRI images are corrupted by periodic noises caused by changes in time constant of electric circuits, unpredictable weather changes and uncertainty of discharging in the cables [15]. The elimination of periodic noise in the acquisition of whole mouse brain is done by Nissl staining test where the intensity value is distributed equally in all brain areas [16]. In strain map analysis the periodic structures highly affect in the form of irregular grid alignment [17].

These periodic structures caused by interferences make changes in several type of imaging process like remote sensed images, Satellite images, SPOT based images, Moderate Resolution Imaging Spectroradiometer (MODIS) for earth observing system, Thematic Mapper (TM) multi spectral images operating in Landsat-4 and 5 satellites [18–20].

The kernel-based filtering techniques not able to remove periodic noises effectively because the periodic noises distributed with uncorrupted image pixels in spatial domain [21]. The repetitive structure of periodic noises can be represented with sinusoidal functions in the frequency domain it can be appeared as spike shaped noisy peaks in the mutually opposite quadrants of frequency spectrum also at the resonant frequency the have highest spectral value. The locations of these spikes based on the frequency of the sinusoidal function. Therefore, these noisy areas can be easily identified with the restoration algorithms operating in frequency domain. Even though this noisy image having symmetric property the band reject filters not producing better results because this type of filters may remove the uncorrupted regions also. Therefore, the statistics-based algorithm was developed which preserve the uncorrupted image details.

The frequency domain mean filter (FDMF1) [22], frequency domain median filter (FDMF2) [23], windowed Gaussian notch filter (WGNF) [24], interpolation filter (IF), Brickwall reject filter (BRF) and Gaussian notch reject filter (GNRF) [25] algorithms. Gaussian star filter (GSF) proposed by Ketenci and Gangal [26] are some statistics-based algorithms. Adaptive Optimum Notch Filter (AONF) [7] used to find the noisy regions with the use of global threshold which can be calculated by taking average of peak values of possible frequency values located outside low-frequency region (LFR). The algorithm proposed by Hudhud and Turner [27] determines noise regions by non-automated procedures.

Chakraborty et al. filter [28] used frequency domain histogram-based thresholding operation for identifying noisy areas, but this method produces misclassifications in noise detection when the noise strength is high.

The identification of noise regions by Sur et al. filter [29], windowed adaptive switching minimum filter (WASMF) [30], Laplacian based frequency domain filter (LFDF) [31], Chakraborty filter [32], Ketenci filter [33] and Ionita filter [34] use static functions but are not adaptive to the noise and image types. Zhou et al. [35] proposed a bilateral linear filter. Chakraborty et al. [36] proposed exponential thresholding based automated notch reject filter. Frequency-domain-based switching median filter [37] applies traditional region-growing technique to generate the noise map.

The filter proposed in [38] by Varghese varying adaptively from the DC coefficient in the centre of the image to the border of the image to identify the corrupted regions.

2 Proposed Method

In this proposed work, the peak signal to noise ratio values computed after image denoising done by Adaptive Gaussian Notch filter with Fourier transform and Curvelet transform were compared.

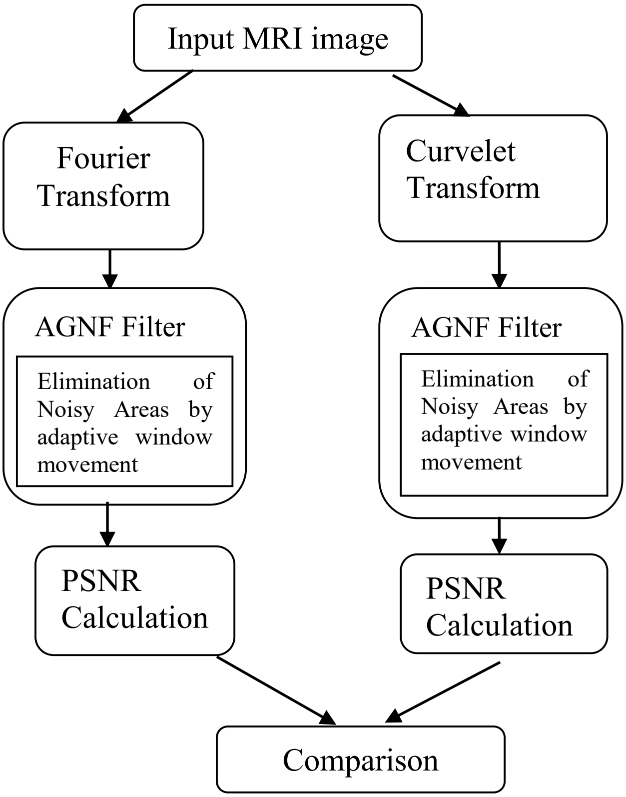

Fig. 1. Work flow of proposed method

The Adaptive Gaussian Notch Filter is used to recognize and identify the noise affected areas by converting the spatial domain of image into frequency domain. After that these noisy frequencies are eliminated with the help of notch filter whose window size is changed in accordance with size of noisy peak areas. For doing filtering function the existing AGNF first converts the image into frequency domain from spatial domain using Fourier transform then move its origin to the middle point of the image. The adaptively varying window filter has inner window W_1 and outer window W_2.With the use of these two windows deviation of frequency from inner neighbourhood to outer neighbourhoods. This algorithm identifies the noisy regions by comparing the ratio of average value of window frequencies with the pre-defined threshold.

The prominent role of Fourier Transform is to represent the image in frequency domain for the identification noise corrupted areas. It is used to describe the image in terms of complex exponentials with different magnitudes, frequencies and phases. After the conversion of frequency domain, the primary work is to reduce the high frequency points to low frequency points to reduce the noise in the image, after performing the necessary steps the image is again transformed to its original form from the frequency domain by using Inverse Fourier Transform.

Curvelet Transform was developed on the basis of Ridegelet Transform, which shows the characteristics of image in multi scale and different angles. Therefore, this transform having numerous directions which eliminates the drawbacks of wavelet transform [40]. Wavelet transform is used to specify point-like singularities while curvelet transform specify curve-like singularities. Also, the wavelet transforms only provide details of scale and location of image while curvelet transform provide information about scale, location and orientation. In general, the image edges are relatively in curve. Therefore, the ridgelet method is not good because it is having single-variable representation while the curvelet transform uses multi scale transform which are designed for higher dimensional functions particularly images which are having large value of discontinuities in curve [41].

The curvelet transform needs less number of co-efficient compared with wavelets and Fourier transform therefore curvelets are well suited especially images having very sharp edges[42],The first generation of Curvelet transform is depends on unequally-spaced Fast Fourier transforms (USFFT) but the next generation uses frequency wrapping of particular Fourier samples.

3 Experimental Results

The results of both Fourier transform based AGNF and Curvelet transform based AGNF outputs were given in fig,2. In this work MRI brain images of New born Baby, Fetal and Adult were considered as input images. The noisy images were obtained by adding Gaussian noise with the input images.

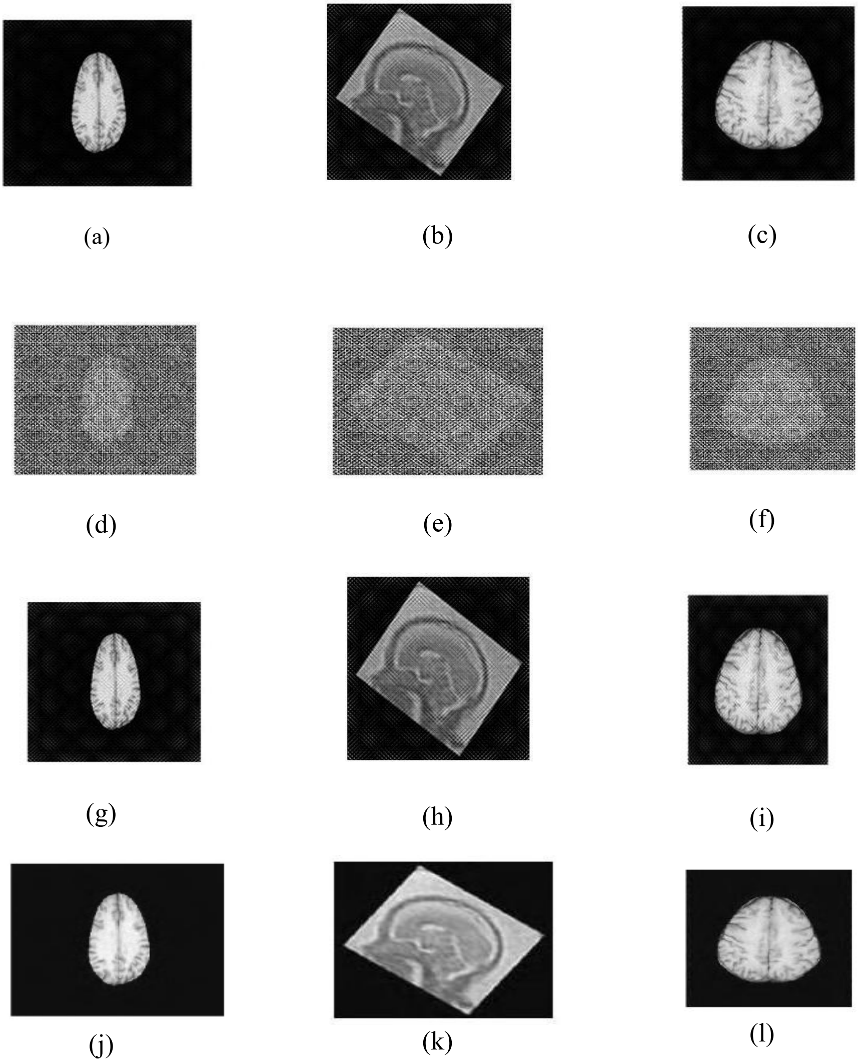

Fig. 2. (a). New Born MRI brain image (b) Fetal MRI image (c) Adult MRI brain image (d)(e)(f) Gaussian Noisy Images (g)(h)(i) Fourier Transform based AGNF filtered Images (j)(k)(l) Curvelet Transform based AGNF filtered Images

4 Evaluation and Validation

In image denoising finding performance metrics from the filtered image is very essential. One of the important quality metrics is Peak Signal to Noise Ratio (PSNR) which can be calculated by using the following formulas.

$$PSNR=10\log_{10}\left(\frac{R^2}{MSE}\right) \quad (1)$$

In the PSNR expression, R denotes largest value of variation in the MRI brain image which value varies based on the data type of the input image. If the image is in floating point type, then the value of R is 1. At the same time if the input image data type is an 8-bit unsigned integer then the R value is 255. Also, in this expression MSE denotes Mean Square Error which gives the cumulative squared error between the filtered and the original image.

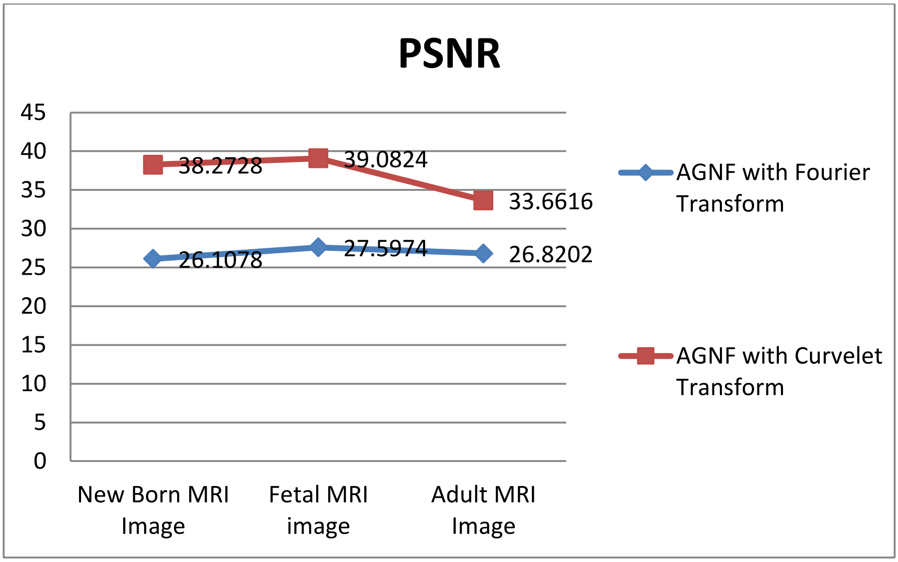

Fig. 3. Comparison curve of PSNR value of AGNF with Fourier transform and Curvelet Transform.

Figure 3 represents the comparison curve of PSNR value of AGNF with Fourier transform and Curvelet Transform. This graph clearly shows that all three i.e. Adult, New

Born, Fetal MRI brain images with Curvelet transform based AGNF produced very high PSNR value compared with Fourier Transform.

5 Conclusion

This paper presented curvelet transform based AGNF for effective image denoising. In this work to identify the noise regions in frequency domain curvelet transform is used instead of Fourier transform. Since curvelet transform is best compared with Fourier and wavelet because of its high directionality which yields high peak signal to noise ratio. Also this filter having the capacity of adaptively changing window size so this filter effectively eliminates noisy peak areas. The results shows that the curvelet transform based AGNF produces high PSNR values for various MRI brain images compared with Fourier Transform.

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