IJCSE International Journal of Computer Sciences and Engineering Open Access
Research Paper Volume-4, Issue-02 E-ISSN: 2347-2693

Suppression of Herringbone Artifact in MR Images of Brain Using Combined Wavelet and FFT Based Filtering Technique

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www.ijcseonline.org

Received: 22/Jan/2016 Revised: 02/Feb/2016 Accepted: 14/Feb/2016 Published: 29/Feb/ 2016

Abstract-Magnetic Resonance Images of Brain often contain herringbone artifact in the form of stripes spread in frequency encoding or phase encoding direction throughout the image. The presence of artifacts create problem in image enhancement and reduces the accuracy of segmentation. In this paper, we propose an efficient, powerful and stable filter based on combined wavelet and Fourier transform for the removal of herringbone artifact. The algorithm strictly separates the features between artifact and original image information and also suppresses the unwanted structures present in the artifact image. It tries to preserve original image information at high degree. The quality of the processed image is evaluated using signal to noise ratio and energy loss measures. The performance and feasibility of the filter are tested on several MR images of brain taken from open source and from radiologists. The results shows that there is a greater improvement in signal to noise ratio and minimal energy loss in the processed image and suggests that the algorithm presented in this paper is suitable in processing and removing herringbone artifact in brain MR images.

Keywords-Magnetic Resonance Imaging (MRI), Herringbone Artifact, Wavelet Transform, Fast Fourier Transform (FFT), Signal to noise ratio (SNR), Energy loss.

I. INTRODUCTON

Magnetic Resonance Imaging (MRI) is a powerful and widely used medical imaging technique in radiology to investigate the anatomy and physiology of the human brain in both health and disease. A wide variety of artifacts are commonly being encountered during MR image acquisition. An artifact is any undesirable feature that appears in an image which is not present in the original imaged object [1]. The presence of artifacts in the image may be confused with pathology or just reduce the quality of examinations. To detect any abnormality in the brain like tumor or lesion, the artifact must be removed or minimized [2]. Artifacts create a problem in the enhancement process and affect segmentation accuracy. Artifacts have some spurious features appeared in the original image. Artifacts are classified as patient related and system related depending on their origin of the cause. Several artifacts occur in MRI [2] but in this paper, system related artifact such as herringbone is considered for removal.

The herringbone artifact is an MRI artifact that appears as a fabric or herring bone throughout the image. It is also called as crisscross artifact or corduroy artifact. The artifact is scattered all over the image in the form of stripes in a single slice or multiple slices in any directionon the image. The herringbone artifact is a term used in MRI for stripe noise or artifact found in other images. The reasons to cause herringbone artifacts are,

- Electromagnetic spikes by gradient coils,
- Fluctuating power supply and
- RF pulse discrepancy.

Successful removal of herringbone artifacts implies that

- Artifact must be disappeared from an image after filtering
- All structural features and the quantitative values of the image information are optimally preserved.

Several different filtering techniques are available to minimize or eliminate the artifact in MR images, such as lowpass filter, moving average filter, histogram matching, interpolation method, frequency filtering with fast FourierTransform as well as wavelets [5-12]. Although different methods give satisfactory results for different images, the basic idea of removal of artifact is that artifact should be known before processing.

It is clearly understood from the above discussion that there is no particular algorithm which can completely tackle the herringbone artifact problem in the MR image. In this proposed method, Wavelet and Fast Fourier transform is

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being used to remove the herringbone artifact in MR images of brain.

II. METHODOLOGY

A. Concept of Wavelet Transform

The wavelet transform has gained widespreadacceptance in signal processing and image processing. Wavelet transform decomposes a signal into a set ofbasis functions. These basis functions are called wavelets. A wavelet is a waveform of effectively limited duration that has an average value of zero. The term 'wavelet' comes from the fact that they integrate to zero; they wave up and down across the axis. Wavelets are obtained from single prototypewavelet called mother wavelet by dilations and shifting. The Wavelet transform is multi-resolution analysisthat can be used to decompose a signal or image into wavelets coefficients and scaling function.

A wavelet function $\Psi(t)$ has two main properties,

$$\int_{-\infty}^{0} \Psi(t)dt = 0; \quad (1)$$

that is, the function is oscillatory or has wavy appearance.

$$\int_{-\infty}^{0} |\Psi(t)|^2 dt < \infty; \quad (2)$$

That is, the most of the energy in $\Psi(t)$ is confined to a finite duration.

A discrete signal f(t) can be approximated bya set of basis functions $\Gamma n(t), n \in \{0,\cdots,N\}$, yielding

$$f(t) \approx \sum_n a_n \cdot \Gamma_n(t) \quad (3)$$

Where the basis functions are orthogonal to each other, that is, the scalar product of every two$\Gamma_n(t)$ meets

$$\langle \Gamma_n(t), \Gamma_m(t) \rangle = \sum_n \Gamma_n(t) \cdot \Gamma_m(t) = \begin{cases} 1, & \forall\, n = m \\ 0, & \forall\, n \neq m \end{cases} \quad (4)$$

Thereby, f(t) will be unequivocally represented by the coefficients a_n.

The main motivation for the decomposition of a signal/image into orthogonal basis functions is thedeployment of the original signal/image information into coefficient classes that specifically groupinteresting structural patterns. This aspect is particularly attractive for artifacts removal techniques. In addition, orthogonal transforms often produces coefficients, which become partly smallor even zero. This characteristic of wavelet analysis makes signal/image decompositionespecially attractive for artifacts removal techniques [13]. Moreover, the calculation of the coefficients is very efficient and achieved in linear timea_n by simple evaluation of scalarproducts:

$$a_n = \langle f(t), \Gamma_m(t) \rangle \quad (5)$$

Furthermore, since Fourier and some wavelet transforms are separable, they can be appliedsuccessively for each dimension in the case of two or more dimensional signals. For the discrete wavelet transform (DWT), a variety of wavelet types exist, which allow perfect reconstruction of the original signal/image, in particular the Daubechies (DB) wavelets shown in figure-1[14] [15].

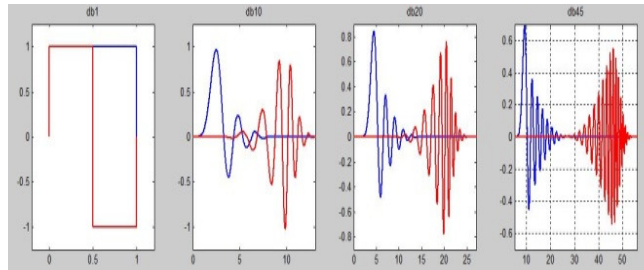

Figure-1Scaling (blue) and wavelet (red) functions of four different types of wavelets: Haar (DB1), DB10,DB20 and DB45.

The image f(r,c) is decomposed into a set of four coefficient images C*l*, C*h*, C*v*, C*d* where C*l* is the low pass filtered image or approximation area which includes information about the global properties of analyzing image, C*h* is the horizontal area which includes information about the vertical lines hidden in image.C*v* is the vertical area which includes information about the horizontal lines hidden in image. C*d*is the diagonal area which includes information about the diagonal details of the image.Therefore, image is divided into 4 sub-sampled spaces, and each piece of the image has dimension (N/2)X(N/2). Thereby, wavelet decomposition of level L produces for image

$$f(r,c) = \sum_m \sum_n C_{l,L,m,n} \cdot \Phi_{l,L,m,n}(r,c) + \sum_m \sum_n C_{h,L,m,n} \cdot \Psi_{h,L,m,n}(r,c) + \sum_m \sum_n C_{v,L,m,n} \cdot \Psi_{v,L,m,n}(r,c) + \sum_m \sum_n C_{d,L,m,n} \cdot \Psi_{d,L,m,n}(r,c) \quad (6)$$

Where, $\Phi_{l,L,m,n}(r,c)$ is the scaling function, $\Psi_{h,L,m,n}(r,c)$, $\Psi_{v,L,m,n}(r,c)$ and $\Psi_{d,L,m,n}(r,c)$ are wavelet coefficients of the image. Consequently, the wavelet representation W of an image f(r,c) results in a set of coefficients

$$f(r,c) \Leftrightarrow W = \{C_{l,L,m,n}, C_{h,L,m,n}, C_{v,L,m,n}, C_{d,L,m,n}\},$$
$$l \in \{1,\cdots,L\} \quad (7)$$

This allows recovery of the original information of the image without loss.Since wavelet transform is separable, the wavelet coefficients in equation(7) are calculated by successive filtering of the image in horizontal and vertical directions applying either low (L) or high pass (H) filters (i.e LL for $C_{l,L,m,n}$, LH for $C_{h,L,m,n}$, HL for $C_{v,L,m,n}$, HH for $C_{d,L,m,n}$) [14] [15].

B. Concept of Fourier Transform

Suppose in f(r,c) with r=0,1, 2,….. M-1 and c= 0,12,….. N-1 specifies the raw image. The two-dimensional Fourier Transform F(u,v) is obtained from the equation (8)

$$F(u,v) = \sum_{r=0}^{M-1} \sum_{c=0}^{N-1} f(r,c)\, e^{-j\omega(\frac{ur}{M}+\frac{vc}{N})} \quad (8)$$

For all u = 0,1,2,……..M-1 and v = 0,1,2,…….N-1.

In fact the Frequency domain is the coordinate systemthat determined byF(u,v) and the frequency variables uand v. This domain is comparable with the spatial domain (the coordinate system defined by the spatial variables r and c). The rectangular M × N area defined by u = 0,1,2,..,M-1 and v = 0,1,2, .., N-1 can be considered as a rectangular frequency. Clearlyrectangular frequency has the same size of the input image [4].

C. Algorithm

Following are the steps to remove herringbone artifact in the vertical direction.

1. Read the Herringbone artifact brain image from the database.
2. Apply Wavelet transform to decompose the image to separate the structural information into horizontal, vertical and diagonal details bands at different resolution scales.
3. Apply FFT to each detailed band which further tights theartifact information into narrow bands.
4. Eliminate the artifact information by multiplying vertical sub region with the Gaussian damping function $g(\hat{r},\hat{c})$given by

$$g(\hat{r},\hat{c}) = 1 - e^{-\left(\frac{\hat{c}^2}{2\sigma^2}\right)} \quad (9)$$

5. Reconstruct the image from the filtered coefficients.
6. Display the resulted image.

D. Separation of Artifact Information

Artifact removal technique uses Fourier transform and coefficient damping as filter to eliminate the artifact exist in image. This filtering technique is applied to all detailed bands since herringbone artifact is scattered throughout the image in any direction.

After each single wavelet decomposition step, the remaining low pass coefficients $C_{l,L,m,n}$still contain the self-similar full image information, yet at a lower resolution. In contrast, all other bands only contain details, i.e. high pass information for getting increased resolution. Hence,the mean image values at lower resolution are still completely preserved when coefficients from the details bands are removed. This is not the case if coefficient damping is performedin the Fourier space only, since these coefficients also contain quantitative information about regional offset values, which will be affected during the filtering process.

E. Assessment of filter quality

For reliable validation of the filter quality, both, qualitative and quantitative aspects are decisive. Qualitatively, the artifact removed images need to be free from artifact, while all other image details have to be preserved. Quantitatively, local mean values of the filtered image away from herringbone artifact must be maintained which is an important requirement for quantitative image analysis [14].

The well-known qualitative method in the Signal processing is signal to noise ratio for images which is given by equation (10)

$$SNR = 10\log 10\left(\frac{\text{Signal Power}}{\text{Noise Power}}\right) \quad (10)$$

where signal power is defined by equation (11) for input image

$$\text{Signal Power} = \sum_{r=0}^{M-1} \sum_{c=0}^{N-1} f(r,c)^2 \quad (11)$$

and noise power is defined by equation (12) for processed image

$$\text{Noise Power} = \frac{1}{MxN} \sum_{r=0}^{M-1} \sum_{c=0}^{N-1} [f(r,c) - f'(r,c)]^2 \quad (12)$$

where, M and N are rows and columns of image matrix. Original image is f(r,c) and processed image is f′(r,c). Equation (12) is also called as Mean Square Error (MSE).

Quantitative evaluation of the results is the total energy of a signal. The loss of the energy can be expressed by the energy of the difference of the original image f(r,c) and the filtered imagef′(r,c), relative to the original one, resulting in the relative mean square error ε_r given by equation(13) [14].

$$\varepsilon_r = \frac{\sum[f(r,c) - f'(r,c)]^2}{\sum f(r,c)^2} \quad (13)$$

F. Choice of Wavelets

There are different types and sizes of wavelets used. The use of Daubechies (DB) wavelets [15] shows visually favorable results even at low energy changes ε_r. The reason for this has not been explored andmay presumably be accompanied with the wavelet smoothness. In figure-6&7, the SNR and energy loss changes for filtering with Daubechies wavelets of different size are displayed.

Observe in figure-6, that SNR is increasing with wavelet filters size and energy loss is decreasing with increasingwavelet filtersize.The wavelet filter is chosen to obtain optimal results.

III. RESULTS AND DISCUSSION

The image database is created by collecting MR images of brain from open source and also from radiologists. The DICOM images are converted into jpeg format. The proposed technique is implemented as a filter on the MATLAB platform. Figure-1 shows brain MR image with herringbone artifact appearing in the form of vertical stripes spread over the entire image.

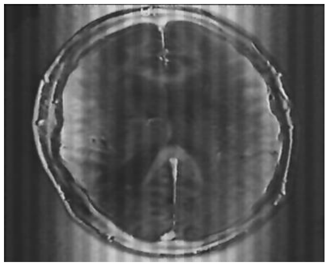

Figure-1 MR image of brain with vertical herringboneartifact

To illustrate the wavelet coefficients, here wavelet filter 'db1' is applied to the input herringbone artifact image shown in figure-1which produces four dyadic detailsshown in figure-2 for decomposition level L =1.

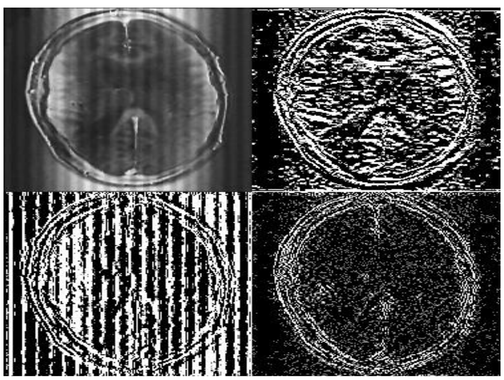

Figure-2 Decomposition up to L=1 is visualized

In the figure-2 decomposition of original image up to 1 level is visualized. Upper left displays the low pass coefficients c_l, the horizontal detail c_h is displayed in the upper right, vertical detail $c_v$is displayed in the bottom left and diagonal detail c_d is displayed in the bottom right. In this example of image, herringbone artifact is present in vertical direction. Vertical detail C_v is distorted by this artifact and can be observed clearly in figure-2 bottom left.

Fourier transform is applied to the vertical detailed coefficients C_v resulted image is shown in figure-3 describes how artifact is completely condensed to the abscissa.

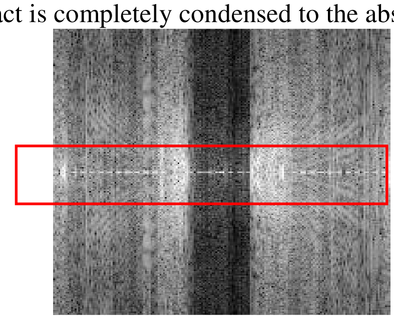

Figure-3 Fourier spectrum showing vertical detail band and artifact component as bright line

Information of the affected herringbone artifact is completely condensed to the abscissa.

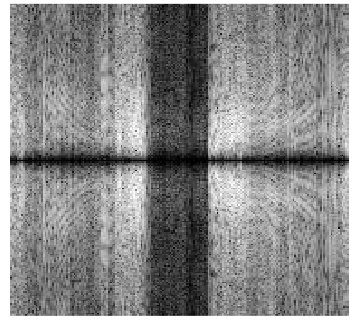

Figure-4Elimination of the artifact after performing damping by using Gaussian function

Information of the affected herringbone artifact is removed by damping of the relevant coefficients by using a Gaussian function. The result after damping is shown in figure-4.

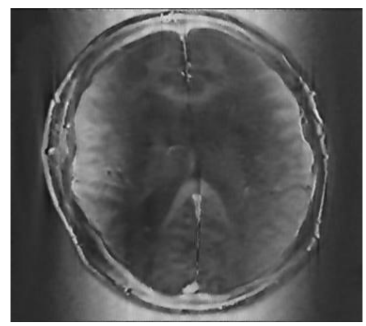

Figure-5Restored image without artifact

Three parameters control the behavior of filtering and accuracy of reconstruction with minimal loss of image information. These parameters are decomposition level ‘L’, wavelet sample type ‘db’ anddamping coefficient‘σ’.

In figure-5 herringbone artifact is eliminated using wavelet filter 'db45'for decomposition level L = 5 and damping factor σ = 6.

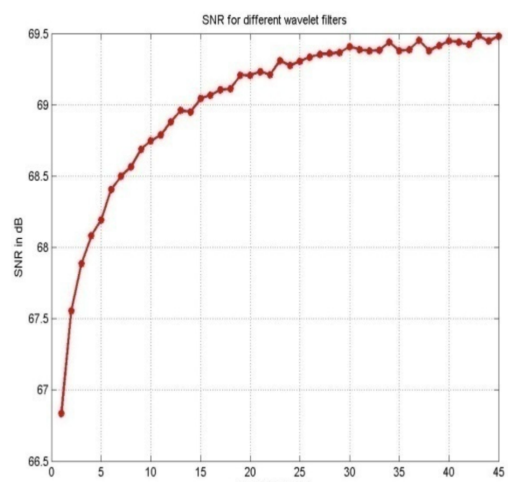

Figure-6 Signal to noise ratio for different wavelet samples for L=5 and σ = 6.

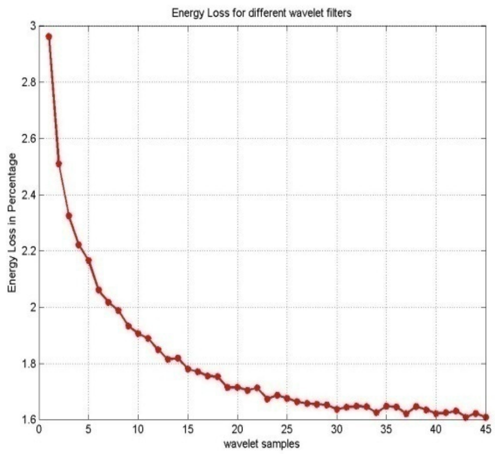

Figure-7 Energy Loss for different wavelet samples for L=5 and σ = 6.

The signal to noise ratio and energy loss for different Daubechieswavelet samples (db1-db45) are calculated for the input image and are shown in figure-6 and figure-7 respectively for decomposition level L = 5 and damping factor σ = 6 (these two parameters are kept constant). Signal to noise ratio is increased with increasing wavelet samples and energy loss is decreased with increasing wavelet samples.

IV. CONCLUSION

The proposed algorithm for removal of herringbone artifact in MR images of brain using wavelet and Fast Fourier transform is a powerful approach in Spectral domain. The algorithm is implemented on MATLAB platform and tested on various herringbone artifact brain MR images taken from open source and also from radiologists. The images are analyzed both qualitatively and quantitatively using signal to noise ratio and energy loss metrics. The graph of SNR and energy loss versuswavelet samples shows thatSNR is increasing and energy loss is decreasing with increasing wavelet size.It is observed that there is a greater improvement in SNR with minimal loss of energy for different wavelet samples.

Three parameters allow controlling the filter behavior and extending its applicability to artifacts: (1) the choice of the wavelet, (2) the highest decompositionlevel L, and (3) the damping factor σ.Optimalresults have been achieved for large Daubechieswavelets (i.e. large number of vanishing moments, at least larger than DB5).

The frequency domain technique preserves the image details. The experimental results suggest that the proposed algorithm is efficient and suitable to remove herringbone artifact which occurs in vertical direction on brain MR Images. The algorithm can be further modified to remove the artifact in horizontal direction.

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