Noise Reduction Techniques in Medical Imaging Data-A Review

Ajay Somkuwar and Shruti Bhargava

***Abstract*—** Noise is an inherent property of medical imaging, and it generally tends to reduce the image resolution and contrast, thereby reducing the diagnostic value of this imaging modality, there is an emergent attentiveness in using multi-resolution Wavelet filters in a variety of medical imaging applications. We Have review recent wavelet based denoising techniques for medical ultrasound, magnetic resonance images, and some tomography imaging techniques like Positron Emission tomography and Computer tomography imaging and discuss some of their potential applications in the clinical investigations of the brain. Our aim is to illustrate and estimate noise suppression methods based on both image processing and clinical expertise.

***Keywords*—**Image denoising, Image Enhancement, wavelets, magnetic resonance imaging, *f*MRI, ultrasound, positron emission tomography, computer tomography.

I. Introduction

IMAGING modalities, such as computed tomography (CT), functional magnetic resonance imaging (fMRI), positron emission tomography (PET), and ultrasonography, have allowed researchers and clinicians to noninvasively evaluate physiological processes within the human body. The rapid development of medical imaging technology and the introduction of new imaging modalities, such as functional magnetic resonance imaging (*f*MRI), calls for new image processing methods including specialized noise filtering, enhancement, classification and segmentation techniques. The majority of fMRI experiments are based on the blood oxygenation level-dependent (BOLD) contrast.. One of the limiting factors regarding performance and usefulness of quantitative MRI diagnostics, such as voxel-based tissue classification, extraction of organ shape or tissue boundaries, estimation of physiological parameters,.

A major source of this type of image degradation is random thermal noise entering the MR data in the time domain (explained in more detail in Section II). The ultimate goal of post-scanning noise removal methods in MRI is to obtain piecewise constant, or slowly varying signals in homogeneous tissue regions while preserving tissue boundaries. However, no single method has shown to be superior to all others regarding noise removal, boundary preservation, robust- ness, user interaction, applicability to the different MR acquisitions techniques, and computation cost.

Ajay Somkuwar, Professor, MANIT, Bhopal. Email: asomkuwar@gmail.com

Shruti Bhargava, Research Scholar, MANIT, Bhopal.

Thus, improvements are still needed.

This paper reviews some of the recent multi-resolution denoising methods for medical ultrasound, MRI imaging, PET imaging and CT imaging and their applications in some clinical investigations of the human brain. It is noteworthy that PET is superior to other imaging modalities in determining physiological functions because readily prepared radionuclides, such as oxygen, carbon, and nitrogen, are essential elements of the human body which are well incorporated into normal physiological processes, Wavelet methods have been previously used to enhance specific features and reduce noise in medical images.

Noise Filtering in Wavelet Province

In mathematics, a wavelet series is a representation of a square-integrals (real- or complex-valued) function by a certain orthonormal series generated by a wavelet. Nowadays, wavelet transformation is one of the most popular candidates of the time-frequency-transformations.The discrete wavelet transform [9–11] translates the image content into an approximation subband and a set of detail sub bands at different orientations and resolution scales. Typically, the band-pass content at each scale is divided into three orientation subbands characterized by horizontal, vertical and diagonal directions. The approximation subband consists of the so-called scaling coefficients and the detail subbands are composed of the wavelet coefficients. Here we consider a non-decimated wavelet transform [10] where the number of the wavelet coefficients is equal at each scale. A general procedure is: Calculate the discrete wavelet transform; Remove noise from the wavelet coefficients and Reconstruct a denoised signal or image by applying the inverse wavelet transform.

The scaling coefficients are typically not modified except for some special imaging modalities like MRI that we address later.

LetW_{kj}^{D}represent the wavelet coefficient at the resolution scale 2^j ($1 \le j \le J$), spatial position$k$ and orientation D.For compactness, we shall omit the indices that denote the scale and the orientation unless in cases where it is explicitly needed.Assume that in each wavelet subband an additive noise model holds

$$W_k = y_k + n_k \qquad (1)$$

Where,$y_k$is the unknown noise-free signal component and $n_k$an arbitrary noise contribution. A majority of the wavelet shrinkage estimators can be represented as

$$\widehat{y_k} = R_k w_k \quad 0 \le R_k \le 1 \qquad (2)$$

Where, $R_k$denotes a *shrinkage factor*. Ideally,$R_k$should be close to zero whenw_k is likely to represent pure noise and it should be close to one when$w_k$is likely to represent a true signal or image discontinuity. For the classical wavelet thresholding rules a threshold value T is defined and $Rk = 0$ is specified as follows.

For *hard thresholding*:

$R_k = 0$ if $|w_k| < T$ and $R_k = 1$ if$|w_k| \ge T$.

For *softthresholding*:

$R_k= 0$ if $|w_k|<T$ and$R_k= 1 - T/|w_k|$ if $|w_k| \ge T$.

One of the first soft-thresholding methods was developed within *medical imaging*, for the noise reduction in magnetic resonance images [21].

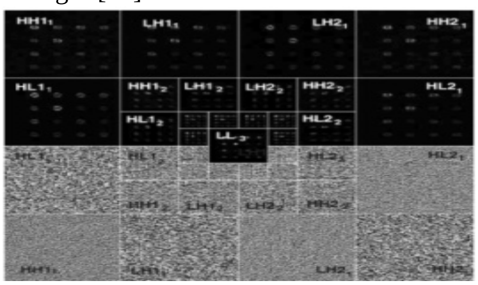

Fig. 1. Subbands representing the magnitude and phase components of a 3-level CWT of a typical microarray image. Here the components are normalized for visualization.

II. Denoising Magnetic Resonance Imaging Data

A. Noise in MRI

The main source of noise in MRI images is the thermal noise in the patient. The MRI image is commonly reconstructed by computing the inverse discrete Fourier transform of the raw data. The signal component of the measurements is present in both real and imaginary channels; each of the two orthogonal channels is affected by additive white Gaussian noise. The noise in the reconstructed complex-valued data is thus complex white Gaussian noise.

In the squared magnitude image, data are non-central chi-square distributed, and the wavelet coefficients are no longer biased estimates of their noise-free counterparts. The bias still remains in the scaling coefficients, but is not signal-dependent and it can be easily removed.

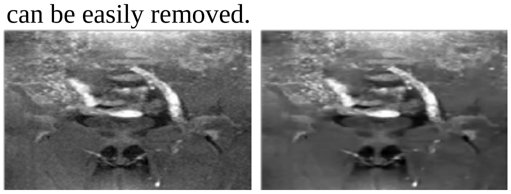

Fig. 2. Left: an original MRI image magnitude. Right: the result of a wavelet denoising method for Rician noise from Section IV-B

B. Noise Reduction via Adaptive Multiscale Products Thresholding

This work presents a wavelet-based multiscale products thresholding scheme for noise suppression of magnetic resonance images. A Canny edge detector-like dyadic wavelet transform is employed. This results in the significant features in images evolving with high magnitude across wavelet scales, while noise decays rapidlythereafter, an adaptive thresholdis calculated and imposed on the products, instead of on the wavelet coefficients, to identify important features [1].

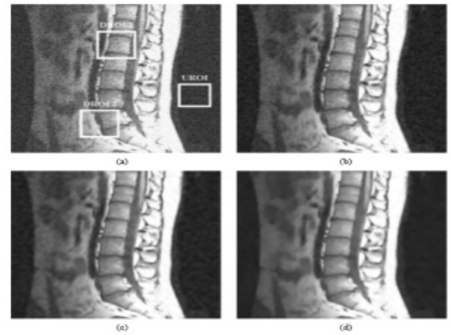

Fig. 3. Experiments on MRI image Spine. The DROI and UROI used to compute the MSR and CNR indexes (listed in Table VI) are highlighted. (a) The noisy image. (b) Estimated by the STH. (c) Estimated by the HTH. (d) Estimated by the presented MPTH.

C. Using Partial Differential Equation (PDE)

This research introduce a new method for image smoothing based on a fourth-order PDE model. The method is tested on a broad range of real medical magnetic resonance images, both in space and time, as well as on nonmedical synthesized test images.

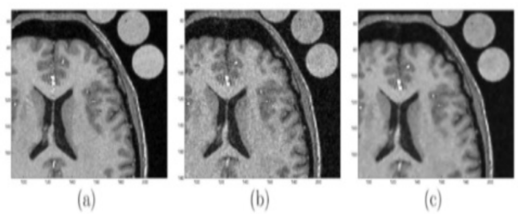

Fig. 4. Evaluation of smoothing algorithm, implemented for isotropic 3-D images. Only one of the 32 contiguous slices, transectioning the lateral ventricles, is shown. (a) AC =4, (b) Input AC =1, and (c) Output 4th order PDE.

This algorithm demonstrates good noise suppression without destruction of important anatomical or functional detail, even at poor signal-to-noise ratio [2].

D. Using Dynamic Non-Local mean Algorithm

This research presents a new algorithm for denoising dynamic contrast-enhanced (DCE) MR images. It is a novel variation on the nonlocal means (NLM) algorithm. The algorithm, called dynamic nonlocal means (DNLM), exploits the redundancy of information in the temporal sequence of images. Empirical evaluations of the performance of the DNLM algorithm relative to seven other denoising methods—simple Gaussian filtering, the original NLM algorithm, a trivial extension of NLM to include the temporal dimension, bilateral filtering, anisotropic diffusion filtering, wavelet adaptive multiscale products threshold, and traditional wavelet thresholding—are presented in the research [3].

TABLE I
MEANS AND FIVE NUMBER SUMMARIES OF THE RANKS ASSIGNED BY ALL OBSERVERS IN EXPERIMENT 3 (MINIMUM, MEAN, MEDIAN, INTERQUARTILE RANGE (IQR) AND MAXIMUM VALUE) TO EACH OF THE DENOISING METHODS IS
TABLE RESULTS TAKEN FROM YANIV GAL, IEEE TRANSACTIONS ON MEDICAL IMAGING, VOL. 29, NO. 2, FEBRUARY 2010.

METHOD	MIN	MEAN	MEDIAN	IQR	MAX
DLNM	2	4.5	5	1	5
ENLM	2	4.3	4	1	5
NLM	1	2.8	3	0	5
GLPF	1	2.2	2	0	5
WAMPT	1	1.1	1	0	4

III. NOISE REDUCTION IN ULTRASOUND IMAGES

A. Speckle Noise in Ultrasound Images

Speckle noise affects all coherent imaging systems including medical ultrasound. Within each resolution cell a number of elementary scatterers reflect the incident wave

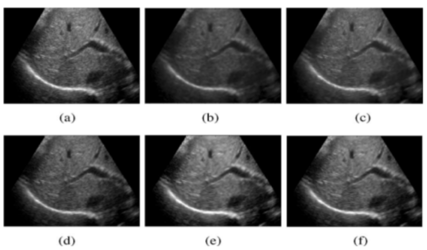

Fig 5. Level of denoising in adjacent preprocessing steps of filtering.

Towards the sensor. The backscattered coherent waves with different phases undergo a constructive or a destructive interference in a random manner. The acquired image is thus corrupted by a random granular pattern, called speckle that hinders the interpretation of the image content.

A speckled image $v= \{v_{1\ldots\ldots\ldots\ldots\ldots\ldots} v_n\}$ is commonly modelled as [7, 10]

$$v_l = f_l \vartheta_l, \tag{3}$$

Where, $\mathbf{f} = \{f_1 \ldots\ldots\ldots\ldots fn\}$ is a noise-free ideal image, and $\vartheta = \{\vartheta_{1\ldots\ldots\ldots\ldots\ldots} \vartheta_n\}$ is a unit mean random field. Modelling the correlated ultrasound speckle is studied in . Some authors assume that realistic spatially correlated speckle noise in ultrasound images can be simulated by low pass filtering a complex Gaussian random field and taking the magnitude of the filtered output.

B. Speckle Noise removal Filters

The best known standard despeckling filters use the second-order sample statistics within a minimum mean squared error estimation approach. Most of the wavelet domain speckle suppression methods apply first the logarithmic transformation. Assuming a purely multiplicative speckle model (III-A) these approaches simplify that the logarithmic operation transforms speckle into additive Gaussian noise. The transformed image is then typically denoised by wavelet thresholding or by a Bayesian wavelet shrinkage [10] which relies on prior distributions for noise-free data.

C. Some Notes on Filtering Medical Ultrasound Images

- *Adaptation to expert defined features of interest*

The desired degree of speckle smoothing should ideally depend on the expert's knowledge and on the application at hand like the enhancement for visual inspection or a preprocessing for an automatic segmentation. For an automatic segmentation it is usually preferred to keep the sharpness of the boundaries between different image regions and to smooth out the speckled texture. For a visual interpretation smoothing the texture may be less desirable.

- *Adaptation to spatial context*

In most "natural" images including the medical ultrasound images there typically exist a significant spatial correlation. A spatially adaptive denoising can be based on statistical context models like Markov random fields or simply on adapting certain filter parameters based on measurements from a local window around each pixel.

IV. DENOISING OF FUNCTIONAL MRI (FMRI) TIME SERIES

A. Analysis of fMRI Data

An fMRI data set is a sequence of three-dimensional (3D) MR images, recorded while the person in the scanner performs a specific task. Most fMRI analysis methods are based on the general linear model (GLM), which models the total brain response as the superposition of all individual stimulus responses. In the GLM, the response to each stimulus is modelled as the output of a linear, time invariant (LTI) system. Such a system is characterised by its impulse response, which, in the case off MRI analysis, is denoted as the haemodynamic response function (HRF).

The analysis of *f*MRI data in the GLM is done via the following formula:

$$\mathbf{Y}_{[TxM]} = \mathbf{X}_{[TxM]}\, \boldsymbol{\beta}_{[MxN]} + \mathbf{e}_{[TxN]} \tag{4}$$

Here, **Y** is the *f*MRI data of *T* time points and *N* voxels (volume elements), **X** is the *design matrix*, whose row vectors are the modelled effects. These may be effects of interests (such as modelled response) and effects of no interest (such as movement-related artefacts or cardiac signals). The matrixβ contains the weight of each effect in each voxel. The residual signal (the part of the signal not modelled in **X**) ends up in the matrix e.

Hypothesis testing may be done with either parametric [5] or nonparametric statistical methods.

B. Denoising of fMRI using Wavelet Denoising and Gaussian Smoothing

Wavelet bases are bases of nested function spaces, which can be used to analyzed signals at multiple scales. Wavelet coefficients carry both time and frequency information, as the basis functions vary in position and scale. The fast wavelet transform (FWT) efficiently converts a signal to its wavelet representation. Here, classified noise into structured and unstructured ones.

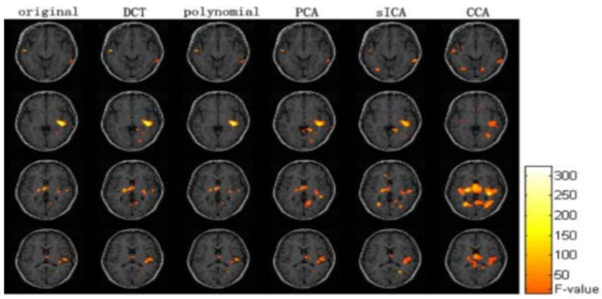

Fig 6. Functional MAP for input fMRI data in system

Canonical correlation analysis was exploited to extract the underlying components among which the structured ones were recognised. Further, the task-related components were detected among the structured ones by using surrogate test based on reduced auto regression model. The low degree of temporal correlation of the unstructured residuals was reduced by using randomization technique.

Time Series of functional MRI Data

A sequence of real MR images was recorded without presenting stimuli. This *null experiment* is assumed to contain only noise [5]. The images are gradient echo EPI images. The time pattern of the activation was made by convolving a randomised stimulus sequence (see fig. 7a) with a haemodynamic response function (HRF). The HRF describes the changes in regional blood flow (and therefore also in the *f*MRI time signal) following a very short stimulus. We model the HRF as the impulse response function of a 4element windkessel [7, 8], which is a damped harmonic oscillator (see fig. 7b). The parameters of the function were chosen so as to resemble some more common HRFs, such as the one composed of two gamma density functions (see fig. 7b). Figure 7c shows the time signal.

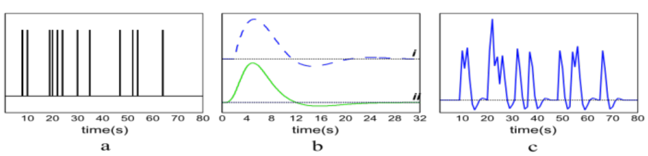

Fig. 7. (a) The stimulus sequence. (b) The damped harmonic oscillator HRF that was used to model the activation (*i*) and the gamma density HRF (*ii*) that was used to estimate the GLM. (c) The modelled response.

C. *Discussion on fMRI denoising*

The results on the tested real MRI sequence, presented above show that despite the various models that exist for fMRI noise (both spatial and temporal), the real case is usually still hard to analyse. When the Genlik method is applied to the squared image (Rician noise version), a large area is detected around the original spot, that is quite different in shape than the original active region. This is due to the local variance component used to predict the local distributions of noise and signal. EPI images have low contrast, and the (erratic) shapes found in the brain bias the classification. The basic Genlik method (applied to the original and not squared image) is much more conservative, and detects only a portion of the original region.

V. Denoising Positron Emission Tomography and other Medical Data

A. *Improving PET-based Physiological Quantification*

This technique also maintained accuracy of flow estimates in comparison with the "gold standard," using dynamic PET with O15-water. In addition, in studies of coronary dis- ease patients, flow patterns were preserved and infarcted regions were well differentiated from normal regions [6].

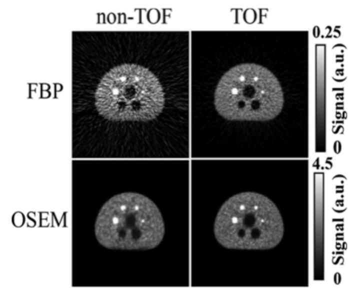

Fig. 8. Example images of the NEMA image quality phantom (200 200 pixels, 4-mm pixel side) without TOF information (left column) and with TOF information (right column), and with FBP (upper row) or OSEM (iteration #5) (bottom row) reconstruction. Random ratio was 1.41.

B. *Wavelet Based Noise Reduction in CT-images*

The projection data measured in computed tomography (CT) and, consequently, the slices reconstructed from these data are noisy. The approach is based on the assumption that data can be decomposed into information, and temporally uncorrelated noise [7]. In CT two spatially identical images can be generated by reconstructions from disjoint subsets of projections: using the latest generation dual source CT-scanners one image can be reconstructed from the projections acquired at the first, the other image from the projections acquired at the second detector. The final noise-suppressed image is reconstructed from the averaged and weighted wavelet coefficients of the input images.

VI. Conclusions

In this paper some practical applications of wavelet domain denoising in ultrasound, fMRI, CT, PET and in MRI imaging were demonstrated. In case of the ultrasound imaging, the interactive noise reduction scheme, taking into account prior information as well as local regional statistics lead to a more naturally ultrasound image, in which anatomical features were better kept intact. While in fMRI &fMRI, wavelet based denoising methods have shown to be effective in terms of improving SNR as well as preserving the shape of the activated region. It has to be mentioned, however, that the results on real fMRI data, where denoising was combined with the statistical parametric mapping. The PET and CT images, researchers evaluated the use of multiscale wavelet transforms on image-based physiological quantification, and provides important information for clinical application.

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