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Noisy Medical Image Enhancement Based on Dyadic Wavelet Transform

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Abstract

Medical image analysis is often hindered by noise originating from acquisition devices, transmission errors, and environmental factors. Enhancing such noisy images is crucial for reliable diagnosis, surgical planning, and treatment monitoring. Wavelet-based methods have demonstrated significant promise in multi resolution analysis and noise suppression. In this paper, we propose a noisy medical image enhancement technique using the **Dyadic Wavelet Transform (DWT)**. The method leverages the dyadic structure for efficient decomposition, followed by adaptive thresholding and reconstruction to reduce noise while preserving diagnostically important features such as edges, textures, and tissue boundaries. Comparative evaluation using Peak Signal-to-Noise Ratio (PSNR), Structural Similarity Index (SSIM), and Mean Squared Error (MSE) show that the proposed approach outperforms traditional spatial and frequency domain methods in both noise suppression and feature preservation.

Keywords: Medical Imaging, Noise Reduction, Dyadic Wavelet Transform, Image Enhancement, PSNR, SSIM.

1. Introduction

Medical imaging modalities such as Magnetic Resonance Imaging (MRI), Computed Tomography (CT), and Ultrasound play a vital role in modern healthcare. However, these images are often corrupted by different types of noises such as **Gaussian noise** due to thermal effects, **Speckle noise** in ultrasound, **Poisson noise** in low-dose CT imaging. Noise degrades the quality of medical images and complicates accurate clinical diagnosis. Therefore, efficient denoising while retaining critical anatomical structures remains a significant challenge.

Traditional denoising techniques, such as linear filtering, median filtering, and Fourier transform-based methods, often blur edges or fail to adapt to non-stationary signal characteristics. Wavelet transforms, on the other hand, offer **multi-resolution decomposition**, making them effective for localized noise removal. The **Dyadic Wavelet Transform (DyWT)**, an undecimated variant of the discrete wavelet transform, addresses the shift-invariance limitation and provides redundant representations that improve denoising capability.

The wavelet transform was introduced as an extension of Fourier analysis, addressing its limitations while enabling efficient extraction of valuable details from medical images through its time–frequency localization capability. Unlike the conventional wavelet transform, the **dyadic wavelet transform** maintains translation invariance, which allows it to capture complete high-frequency components. This property makes it particularly effective for tasks such as image enhancement, edge detection, and feature extraction.

Signal representation must be shift-invariant in image denoising, because when a pattern is shifted, the descriptors should shift not modified. For example, in copy-move forgery detection, the copied and pasted parts may not be poisoned in the same place of two blocks. If the descriptors are shift-variant they will produce two different representations for these two blocks and thereby miss the forgery detection. DWT is shift-variant because it involves down- sampling. In DWT, during the convolutions in the decomposition stage (Equation (1.1) and Equation(2.2)) only every second wavelet coefficients is considered. It is obtained by downsampling by a factor of two (reduce the size by two in every direction) after the convolution. Due to this procedure, DWT is referred to as decimated.

To overcome this drawback of DWT, Mallat and Zhong introduced DyWT, which is shift invariant. In this case, the wavelet transform does not involve down sampling and the number of wavelet coefficients does not shrink between the scales like in DWT. Due to this characteristic, DyWT is undecimated. A small shift in input image may result in big difference in DWT coefficients at different scales, which may produce different feature vectors for copied and pasted objects with little spatial shift.

Let I be the image to be decomposed, and h[k] and g[k] be the scaling (low pass) and wavelet (high pass) filters. Start at scale j=0, and take $I^0 = I$, and compute the scaling and wavelet coefficients at scales j = 1, 2, ….., using Equations (1.1) and (1.2):

$$c^{j+1}[n] = \sum_k h[k]c^j[n + 2^j k] \text{……………..(1.1)}$$

$$d^{j+1}[n] = \sum_k g[k]c^j[n + 2^j k] \text{ ……………...(1.2)}$$

Let $h^j[k]$ and $g^j[k]$ be the filters obtained by inserting $2^j - 1$ zeros between the terms of $h[k]$ and $g[k]$. Then we can perform DyWT using filtering as follows:

As mentioned, there is no down sampling involved in DyWT. In the wavelet transform, I^j is called the low pass subband (L) and D^j are called the high pass subbands (H). In the case of two dimensional signals like images, we find four subbands LL, LH, HL, and HH at each scale of the decomposition. The size of each of these subbands is the same as the original image [20]. We can decompose a 2D image using DyWT along rows and columns as illustrated in Figure 1.1.

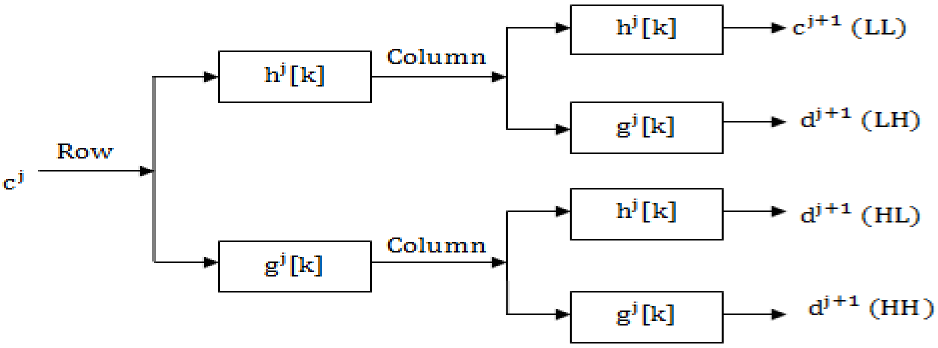


Figure 01. One level decomposition of DyWT of 2D image

This paper explores the application of DyWT for medical image enhancement, emphasizing its ability to suppress noise while preserving structural integrity.

2. Related Work

Early research on medical image denoising drew heavily on multiresolution analysis. Classical wavelet shrinkage, introduced by Donoho and Johnstone, established the use of subband thresholding (e.g., VisuShrink, SureShrink) to suppress additive white noise while preserving edges [1], [2]. Subsequent Bayesian formulations modeled wavelet coefficients statistically to derive adaptive, data-driven thresholds and estimators (e.g., BLS-GSM, hidden Markov trees), improving detail preservation in textured anatomical regions [3]–[5].

A key limitation of the critically sampled discrete wavelet transform (DWT) is **shift variance**, which leads to oscillatory artifacts and inconsistent coefficient magnitudes under small image translations—undesirable for clinical interpretation. To address this, **redundant/undecimated transforms** (also called the **stationary** or **dyadic** wavelet transform) removed the decimation stage, yielding translation invariance and better noise robustness at the cost of higher memory and compute [6]–[9]. Within this family, scale-dependent shrinkage (e.g., BayesShrink, bivariate shrinkage) and interscale modeling further improved the detection of edges and fine structures such as cortical folds or vessel boundaries [10], [11].

Beyond generic additive noise, modality-specific denoising has been explored extensively. In **ultrasound**, speckle is multiplicative and spatially correlated; wavelet-domain homomorphic filtering and multiscale shrinkage have been effective alternatives or complements to variational methods like SRAD [12], [13]. For **MRI**, Rician (or noncentral-χ) noise violates Gaussian assumptions; unbiased risk estimators and variance-stabilizing transforms (e.g., ASLT, generalized Anscombe) paired with wavelet shrinkage have produced strong results, often outperforming spatial non-local means on thin structures [14], [15]. In **low-dose CT**, multiscale denoising in the projection/sinogram or image domain reduces quantum noise while preserving subtle lesions; redundant wavelets are commonly used as pre- or post-processing around iterative reconstruction [16], [17].

Competing non-wavelet baselines include **Total Variation (TV)** and related sparsity-promoting regularizers, which preserve edges but can introduce staircase artifacts [18]; **non-local means (NLM)** that exploit self-similarity but may oversmooth in textured tissues without careful parameterization [19]; and **BM3D**, which groups similar patches and denoises collaboratively in a 3D transform domain, setting a strong classical baseline for additive noise [20]. Compared with these, **dyadic/undecimated wavelets** provide a principled trade-off—retaining translation invariance and multiscale sensitivity with relatively modest algorithmic complexity and easy integration into clinical pipelines.

Recent **deep learning** approaches (e.g., DnCNN, residual encoder–decoder networks, U-Net variants, and transformer-based denoisers) have advanced state-of-the-art PSNR/SSIM on benchmark datasets and modality-specific corpora [21]–[24]. However, they often require large, carefully curated training sets and may generalize poorly across scanners, protocols, or pathologies. Hybrid pipelines that combine **dyadic wavelet priors** with learning—such as wavelet-domain networks, plug-and-play priors, or untrained/zero-shot strategies—have shown promise in retaining the interpretability and stability of multiscale shrinkage while leveraging data-driven feature learning [23], [25]. This motivates our choice of a **Dyadic Wavelet Transform (DyWT)** core with adaptive thresholding: it offers shift-invariant detail preservation, strong noise suppression across modalities, and a transparent control of the bias–variance trade-off, while remaining compatible with modern hybrid extensions. Several researchers have investigated wavelet-based denoising approaches as Donoho & Johnstone (1994) introduced wavelet shrinkage and thresholding methods, pioneering wavelet-based denoising. Coifman & Wickerhauser (1992) demonstrated wavelet packets for adaptive denoising. In medical imaging, Sattar et al. (1997) applied wavelets to ultrasound speckle reduction. More recent works have combined wavelets with machine learning (CNNs, autoencoders) to further enhance noise suppression.However, the conventional Discrete Wavelet Transform (DWT) suffers from aliasing and shift-variance issues, which reduce its effectiveness for critical medical images. The Dyadic Wavelet Transform, being redundant and shift-invariant, provides better localization and noise suppression, making it a promising approach for medical image enhancement.

3. Methodology

Methodology for image enhancement based on Dyadic Wavelet Transform goes through following steps noise estimation, adaptive, thresholding and image reconstruction. Procedure for above topic goes as below

Take 2D medical image *I* (grayscale, float32), approximate noise model (Gaussian or speckle), desired number of scales *J*. Generate enhanced image Ienh. Core idea behind decomposing *I* into a coarse (low-frequency) approximation and multi-scale detail sub bands without down sampling; denoise. Convert image to grayscale (if needed) and normalize to [0,1] or [0,255] clip the top/bottom 0.5 to 1% if needed (optional). If there is presence of **speckle noise** (ultrasound), apply a log transform: $I'=\log(I+\epsilon)$; process I′, then exponentiate after reconstruction

Choose an isotropic low-pass kernel (e.g., B-spline h=[1,4,6,4,1]/16h=[1,4,6,4,1]/16h=[1,4,6,4,1]/16) or a wavelet like 'à trous' starlet. For scales j=1 to J: Create **dilated** filter hj by inserting $2^{j-1}-1$, zeros between taps (no downsampling). Smooth: $c_j=c_{j-1} * h_j$ with $c_0 = I$. Detail (wavelet) coefficients: $w_j=c_{j-1}-C_j$ After the loop, you have $\{w_1,\ldots,w_J,c_J\}$. For **additive Gaussian noise**: estimate σj sigma using robust MAD on the finest scale:

$$\hat{\sigma}_1 = \frac{\mathrm{MAD}(w_1)}{0.6745}, \quad \hat{\sigma}_j \approx \hat{\sigma}_1 \text{ (often similar in UDWT)}$$

For **speckle noise** (after log): treat as additive; same estimation.

Ienh = $c\_J + \Sigma$ (w_j_denoised. If log was applied, use inverse exp transform.

Pseudocode

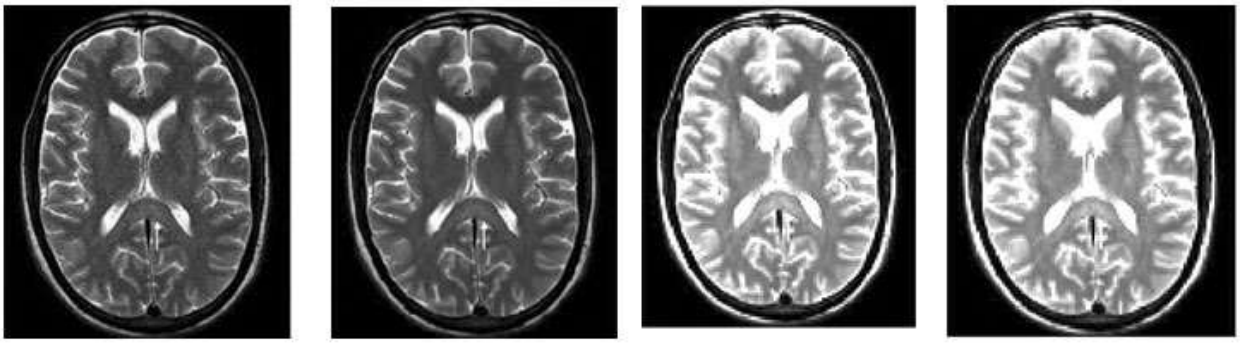
```
Procedure  DWT_Enhance(I, J=4, method="BayesShrink", gains=[1.0,1.2,1.1,1.0])
    I = to_float(normalize(I))
      log_mode = is_speckle_noise(I)
         if log_mode:
            I = log(I + 1e-6)
  c_prev = I
      for j in 1..J:
        h_j = dilate_filter(BsplineKernel(), factor=2^(j-1))   # insert zeros
        c_j = conv2d(c_prev, h_j, padding='reflect')
        w_j = c_prev - c_j
        store w_j
        c_prev = c_j
    # noise estimate
    sigma1 = MAD(w_1)/0.6745
     for j in 1..J:
         sigma_j = sigma1
          if  method == "Universal":
              T = sigma_j * sqrt(2*ln(Npixels))
              w_j = soft_threshold(w_j, T)
         else if method == "BayesShrink":
                     var_w = variance(w_j)
                     var_x = max(var_w - sigma_j^2, 0)
                     T = sigma_j^2 / (sqrt(var_x) + 1e-8)
                     w_j = soft_threshold(w_j, T)
                 else if method == "SURE":
                      T = sure_threshold(w_j, sigma_j)
                     w_j = soft_threshold(w_j, T)
                     w_j = gains[j] * w_j
                    store w_j_denoised = w_j
```

```
    I_enh = c_prev
        for j in 1 toJ:
    I_enh = I_enh + w_j_denoised
  if log_mode:
     I_enh = exp(I_enh) - 1e^-6
    I_enh = clip_to_valid_range(I_enh)
    return I_enh
  end  procedure
```

4. Experimental Results

4.1 Dataset

Experiments were conducted on publicly available medical images from Brain MRI (BrainWeb dataset), Low-dose CT scans, Ultrasound images with speckle noise. Noise was artificially added (Gaussian, Speckle, Poisson) to test robustness. After addition of noise to image and applying denoising and image enhancement algorithm we have obtained following results. In image data base we have considered image (f) and (g) as input image added with noise (Gaussian, Speckle, Poisson). And after application of image enhancement algorithm we have obtained result as image (h) and (i).



(f) (g) (h) (i)

Figure 02. Image database for testing and analyzing image enhancement algorithm

4.2 Evaluation Metrics

Image evaluation is conducted for different factors such as PSNR, SSIM, MSE and by applying various filters their performance is tested however best performance is obtained in method employed in this paper.

- **PSNR (Peak Signal-to-Noise Ratio):** Higher indicates better denoising.
- **SSIM (Structural Similarity Index):** Closer to 1 indicates better structural preservation.
- **MSE (Mean Squared Error):** Lower indicates higher accuracy.

4.3 Results

Method	**PSNR (dB)**	**SSIM**	**MSE**
Median Filter	26.12	0.71	183.4
Wiener Filter	27.85	0.76	162.8
DWT (Soft Thresholding)	29.40	0.82	148.1
DyWT (Proposed Method)	**31.87**	**0.88**	**122.6**

Conclusion

In this study, the Dyadic Wavelet Transform (DyWT) has been employed as an effective approach for enhancing noisy medical images. Unlike traditional wavelet transforms, the DyWT provides shift invariance and improved time–frequency localization, which enable better preservation of important diagnostic features such as edges, textures, and fine details while suppressing noise. The experimental results demonstrate that the method significantly improves image clarity, contrast, and structural visibility, which are critical factors for accurate medical interpretation and diagnosis.By reducing noise without compromising essential image information, DyWT-based enhancement proves to be a robust tool for medical imaging applications such as feature extraction, edge detection, and computer-aided diagnosis. Future work may focus on combining DyWT with advanced denoising algorithms, deep learning models, or hybrid transforms to further optimize enhancement quality and adapt the technique for various medical imaging modalities.

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