Proceedings of the Twelfth International Conference on
Engineering Computational Technology
Edited by: P. Iványi, J. Kruis and B.H.V. Topping
Civil-Comp Conferences, Volume 8, Paper 7.2
Civil-Comp Press, Edinburgh, United Kingdom, 2024
ISSN: 2753-3239, doi: 10.4203/ccc.8.7.2

Fuzzy Logic Method for Speckle Noise Reduction in Ultrasound Images and Its Parallel Implementation on Multi-Cores

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Abstract

This paper presents a parallel method aimed at reducing speckle noise in ultrasound medical images, utilizing fuzzy logic and the fuzzy peer group concept. The method is implemented on multi-core interfaces using Open Multi-Processing. The efficiency of the method is evaluated based on execution time, Mean Squared Error, and Peak Signal-to-Noise Ratio. The evaluation is conducted on medical images from the Ultrasoundcases database that have been contaminated with speckle noise. Experimental results demonstrate that the proposed method obtains good performance in terms of the aforementioned objective quality measures. Furthermore, the application of multi-core optimization strategies shows that the new filter can reduce speckle noise in real-time.

Keywords: parallel computing, fuzzy logic, medical ultrasound imaging, noise reduction, speckle noise, speckle reduction.

1 Introduction

Medical ultrasound (US) images are adversely affected by speckle noise, which degrades their quality and can obscure vital information essential for accurate diagnosis.

The application of effective filtering techniques is crucial for enhancing diagnostic capabilities. Consequently, the reduction of speckle noise is a vital component in the processing of ultrasound images.

Numerous methods have been proposed for speckle noise reduction in ultrasound images. Many of these methods rely on local statistics, such as those by Lee [1], Frost [2], Kuan [3], median filter [4,5], bilateral filter [6], speckle reducing anisotropic diffusion (SRAD) [7], oriented SRAD (OSRAD) [8], squeeze box filter (SBF) [9, 10], and guided filter [11, 12]. Additionally, wavelet-based approaches have demonstrated significant potential for speckle denoising [13–15]. Another notable category of filters for speckle noise reduction includes those based on the classical nonlocal means (CNLM) filter [16]. Although the CNLM filter was not initially designed for speckle noise, several studies have adapted it for this purpose [17, 18].

In [19], the authors introduced a color image filter for the reduction of mixed Gaussian-impulse noise, termed Fuzzy Peer Group Averaging Filter (FPGA), which utilized the fuzzy peer group concept. Experimental results indicated that this technique delivered competitive performance in processing mixed Gaussian-impulse noise in color images compared to other state-of-the-art methods. However, its efficacy has not been evaluated in the context of speckle noise. In this study, we propose a speckle noise filtering method inspired by the concept presented in [19]. The proposed method calculates the optimal number of components in the peer group using a fuzzy logic process, followed by a smoothing process employing only the best pixels from the peer group.

Moreover, sequential computers are inadequate for executing this algorithm in the real-time requirements of medical applications. To address this issue, we introduce a parallel algorithm aimed at enhancing computational efficiency to make it suitable for real-time medical processing. This parallel algorithm has been implemented for shared-memory architectures using Open Multi-Processing (OpenMP). Results obtained on a multi-core system demonstrate that the parallel algorithm achieves efficiencies ranging from 74.75 to 80.37 for different ultrasound images.

Section 2 provides a detailed description of the filter design. The experimental results are presented in Section 3, and the conclusions are discussed in Section 4.

2 Methods

In this section we overview the formulations of the proposed method and its parallel implementation.

2.1 Fuzzy method

Consider a grayscale image I defined as a mapping $\mathbb{Z}^2 \to \mathbb{Z}$. This means the image is represented by a matrix I of size $M \times N$ consisting of pixels x_i, indexed by i, that specify the pixel positions within the image domain Ω. The pixel value x_i, for $i = 1, 2, \ldots, M \times N$, quantized into the integer domain, denotes the pixel intensity. To reduce speckle noise, a fuzzy averaging among the pixels of the fuzzy peer group is performed. Algorithm 1 presents the filtering algorithm. The subsequent paragraphs detail the steps of this algorithm.

Require: Image I, parameter F_σ
Ensure: Filtered image
for each pixel x_i in I **do**
  Compute $\widehat{m}$, the optimal number of pixels for $\mathcal{P}(m, x_i)$
  $\widehat{m} = \arg\max_{m \in N_W} C_{FR1}(m)$
  Speckle Noise Smoothing:
  $x_{\text{out}} = \frac{\sum_{j=0}^{\widehat{m}} FP_{\widehat{m}}^{x_i}(x_{(j)}) x_{(j)}}{\sum_{j=0}^{\widehat{m}} FP_{\widehat{m}}^{x_i}(x_{(j)})}$
end for

Algorithm 1: Speckle denoising method

Let W be a filtering window of $n \times n$ pixels centered at pixel x_0. Let $x_i \in W$, for $i = 1, \ldots, n^2 - 1$, represent the neighboring pixels of x_0. The proposed method utilizes the fuzzy peer group concept as described in [19] and employs a fuzzy metric.

The peer group concept [20] is based on ordering neighboring pixels according to their similarity to the central pixel x_0. Let S be an appropriate similarity measure [21] between two pixels. Pixels $x_i \in W$ are ordered in descending order based on their similarity to x_0. This results in an ordered set $W' = \{x_{(0)}, x_{(1)}, \ldots, x_{(n^2-1)}\}$, where $S(x_0, x_{(0)}) \geq S(x_0, x_{(1)}) \geq \ldots \geq S(x_0, x_{(n^2-1)})$, and $x_{(0)} = x_0$.

According to the peer group concept [20], the peer group $\mathcal{P}(m, x_0)$ of $m + 1$ pixels associated with x_0 is defined as:

$$\mathcal{P}(m, x_0) = \{x_{(0)}, x_{(1)}, \ldots, x_{(m)}\}. \tag{1}$$

In [19], a fuzzy logic algorithm is introduced to compute the optimal number of pixels $\widehat{m}$ in a peer group. The fuzzy peer group for the central pixel x_0 in a window W is given by the fuzzy set $\mathcal{FP}(\widehat{m}, x_0)$ determined on the set $\{x_{(0)}, x_{(1)}, \ldots, x_{(\widehat{m})}\}$ and defined by the membership function $FP_{\widehat{m}}^{x_0} = S(x_0, x_{(i)})$.

The optimal number $\widehat{m}$ of pixels in $\mathcal{P}(m, x_0)$ is determined as the number $m \in \mathcal{N}_W = \{1, 2, \ldots, n^2 - 1\}$ that maximizes the certainty of the Fuzzy Rule FR1.

Fuzzy Rule FR1: *Certainty for m to be the best number of pixels in $\mathcal{P}(m, x_0)$*

IF "x_m is similar to x_0" and the *accumulated similarity* for $x_{(m)}$ is large

THEN "the certainty for m to be the best number of pixels for $\mathcal{P}(m, x_0)$ is high".

$C_{FR1}(m)$ represents the certainty of Fuzzy Rule FR1 for m. Then, $C_{FR1}(m)$ is computed for each $m \in \mathcal{N}_W$, and the m that maximizes the certainty is chosen as the optimal number $\widehat{m}$ of pixels in $\mathcal{P}(m, x_0)$, i.e., $\widehat{m} = \arg\max_{m \in N_W} C_{FR1}(m)$.

The certainty of " x_m is similar to x_0" is determined by the membership function C^{x_0} given by the similarity function:

$$C^{x_0}(x_{(i)}) = S(x_0, x_{(i)}),\ i = 0, 1, \ldots, n^2 - 1. \tag{2}$$

The accumulated similarity for $x_{(m)}$, denoted by $H^{x_0}(x_{(m)})$, is given by:

$$H^{x_0}(x_{(i)}) = \sum_{k=0}^{k=i} S(x_0, x_{(k)}),\ i \in \{0, 1, \ldots, n^2 - 1\}. \tag{3}$$

Then, the certainty of " $H^{x_0}(x_{(m)})$ is large" is determined by the membership function μ^{x_0} defined as:

$$\begin{aligned} \mu^{x_0}(x_{(i)}) &= -\frac{(H^{x_0}(x_{(i)}) - 1)(H^{x_0}(x_{(i)}) - 2n^2 + 1)}{(n^2 - 1)^2} \\ & \quad i = 0, 1, \ldots, n^2 - 1. \end{aligned} \tag{4}$$

The product t-norm is used as the conjunction operator, thus no defuzzification is required. Therefore, $C_{FR1}(m) = C^{x_0}(x_{(m)})\mu^{x_0}(x_{(m)})$.

The fuzzy similarity function employed is:

$$S(x_i, x_j) = e^{-\frac{\|x_i - x_j\|}{F_\sigma}} \quad i, j = 0, \ldots, n^2 - 1, \tag{5}$$

where $\| \cdot \|$ denotes the Euclidean norm, and F_σ is a parameter analyzed in Section 3. This function is chosen because it is a fuzzy metric [22], which has been demonstrated to be suitable for fuzzy image processing [19, 23]. The similarity S ranges in the interval $[0, 1]$, and $S(x_0, x_i) = 1$ if and only if $x_0 = x_i$.

2.2 Parallel Implementation

To describe the parallel method, the image domain Ω is divided into P subdomains $\{\Omega_i\}_{i=1}^{P}$, where P represents the number of computation elements. This domain decomposition satisfies:

$$\Omega_i \subset \Omega,\ \bigcup_{i=1,2,\ldots,P} \Omega_i = \Omega,\ \text{and } \Omega_i \cap \Omega_j = \emptyset \text{ for } i \neq j. \tag{6}$$

Figure 1 illustrates an example of the decomposition used in the numerical experiments. In this example, the image is divided into four subdomains.

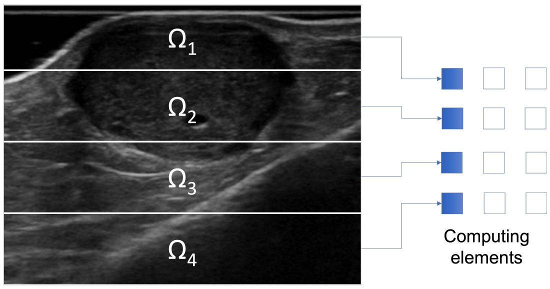
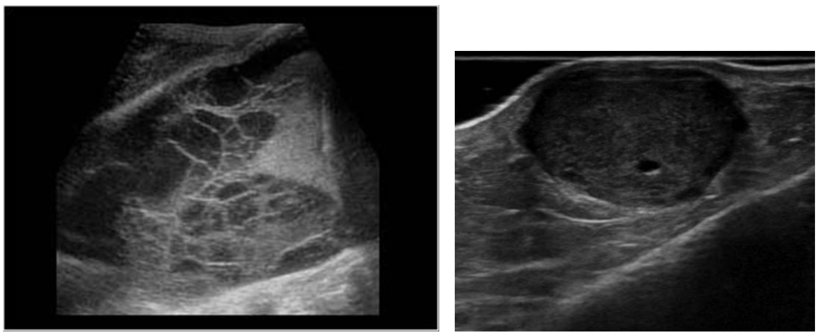


Figure 1: Image domain decomposition: Distributed image on 4 computing elements

3 Experiments

We have implemented the parallel version of the algorithm on a multi-core platform using OpenMP [24]. Both the serial and parallel codes were developed in C, utilizing GNU C Compiler (GCC) version 7.5.0. The experiments were conducted on a multi-core Intel Xeon CPU X5660 (12 cores), operating at 2.8 GHz, with 48 GB RAM, running CentOS Linux version 5.6. Various real ultrasound images sourced from the UltrasoundCases database [25] were used in the experiments (see Figure 2). These images were artificially corrupted with different levels of speckle noise, with variances $\sigma = 0.2$, $\sigma = 0.4$, $\sigma = 0.6$, and $\sigma = 0.8$.



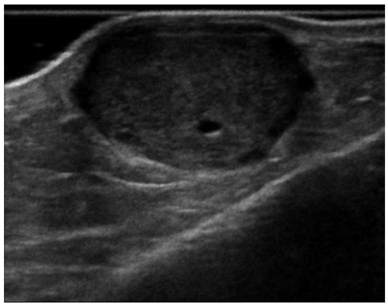
(a) US 1 (450×600 pixels) (b) US 2: 378×484 pixels

Figure 2: Ultrasound images used in experiments.

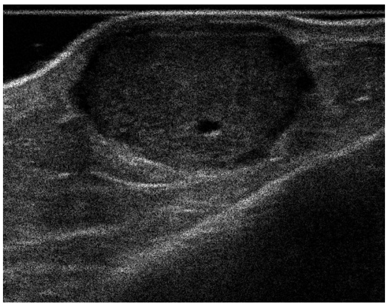
To optimize the input parameter F_σ in Equation (5), the algorithm's performance was evaluated in terms of Peak Signal-to-Noise Ratio (PSNR) as a function of F_σ. The optimal results were achieved for $F_\sigma = 400$. The parallel performance was assessed by computing the speed-up S_P as $S_P = T_{seq}/T_P$, where T_{seq} is the computational time of the sequential method, and T_P is the computational time of the parallel algorithm.

Figure 3 displays the filter outputs for the US 2 image, which has been contaminated with various levels of speckle noise ($\sigma = 0.2$, $\sigma = 0.4$, $\sigma = 0.6$ and $\sigma = 0.8$) for visual comparison. The results demonstrate the effective denoising performance of the proposed algorithm, while also preserving the edges and contours of the image.

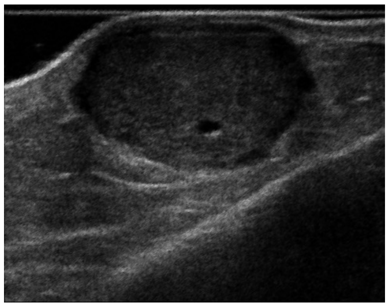
(a) noisy image, $\sigma = 0.2$



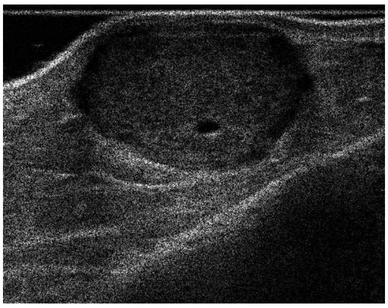
(b) filter ouput



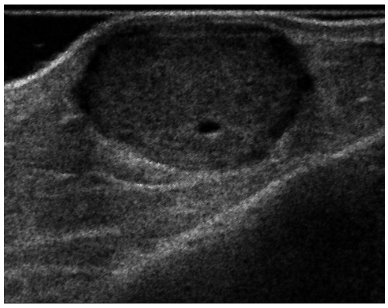
(c) noisy image, $\sigma = 0.4$



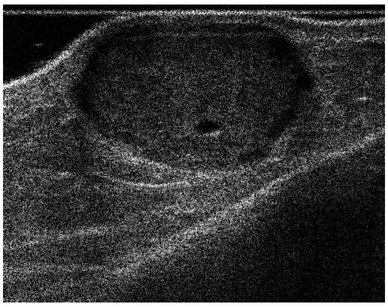
(d) filter ouput



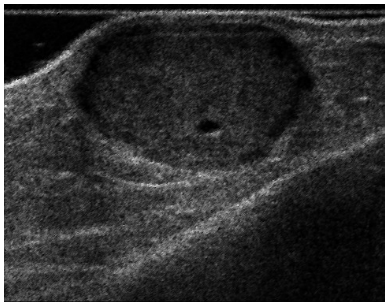
(e) noisy image, $\sigma = 0.6$



(f) filter ouput



(g) noisy image, $\sigma = 0.8$



(h) filter ouput

Figure 3: Filter outputs for visual comparison. Image US 2 contaminated with various levels of speckle noise with variance σ.

Table 1 presents the denoising performance metrics in terms of mean-square error

(MSE) and PSNR [21] for ultrasound images corrupted with varying levels of speckle noise. The consistently low MSE values and high PSNR values across all noise levels indicate the robust denoising capability of the proposed algorithm. These findings were consistent across all tested images.

		US 1		US 2	
Noise	Image	MSE	PSNR	MSE	PSNR
$\sigma = 0.2$	Noisy	179.2	25.59	155.4	26.21
	Filtered	7.7	29.82	30.6	33.26
$\sigma = 0.4$	Noisy	680.8	19.80	574.0	20.54
	Filtered	129.6	27.00	76.1	29.31
$\sigma = 0.6$	Noisy	1352.4	16.81	1150.2	17.52
	Filtered	220.2	24.70	144.3	26.53
$\sigma = 0.8$	Noisy	2065.8	14.97	1793.4	15.59
	Filtered	324.7	23.01	228.35	24.54

Table 1: Quality measures MSE and PSNR for US images contaminated with speckle noise $\sigma = 0.2$, $\sigma = 0.4$, $\sigma = 0.6$ and $\sigma = 0.8$.

Table 2 show the computational time, speed-up and efficiency obtained for the test ultrasound images contaminated with different level of speckle noise (variance $\sigma = 0.2$, $\sigma = 0.4$, $\sigma = 0.6$ and $\sigma = 0.8$). It can be observed that the level of noise does not affect the speed-up. This fact is due to the characteristics of the filter. Results show that the parallel algorithm achieves speed-ups in the range 8.97 to 9.64 when the 12 cores of the multi-core system are used.

Noise	Image	Sequential time	Parallel time	Speed-up	Efficiency
$\sigma = 0.2$	US 1	1.2323	0.1320	9.33	77.79
	US 2	0.8423	0.0939	8.97	74.75
$\sigma = 0.4$	US 1	1.2398	0.1298	9.54	79.54
	US 2	0.8498	0.0890	9.54	79.51
$\sigma = 0.6$	US 1	1.2401	0.1304	9.50	79.22
	US 2	0.8500	0.0894	9.49	79.14
$\sigma = 0.8$	US 1	1.2498	0.1295	9.64	80.37
	US 2	0.8499	0.0906	9.37	78.16

Table 2: Computational time in seconds, speed-up and efficiency for US images contaminated with speckle noise $\sigma = 0.2$, $\sigma = 0.4$, $\sigma = 0.6$ and $\sigma = 0.8$.

4 Conclusions

A parallel method based on fuzzy peer groups and fuzzy logic has been presented to reduce speckle noise in medical ultrasound images. The method has been implemented on multi-cores using OpenMP. The implementation has been applied to reduce speckle noise on ultrasound images from the Ultrasoundcases database. The filter obtained robust results in terms of the objective quality mesures MSE and PSNR. The parallel algorithm achieved significant speed-ups, reducing computational times and rendering the method suitable for real-time medical image processing. Future work will focus on implementing the algorithm on GPUs using CUDA.

Acknowledgements

This research was supported by the Spanish Ministry of Science and Innovation (Grant PID2021-123627OB-C55) co-financed by FEDER funds and by the University of Alicante (Grants UAUSTI22-02, UADIF23-09 and VIGROB23-020).

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