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**RESEARCH ON SOME ULTRASOUND TOMOGRAPHY IMAGE
RECONSTRUCTION METHODS BASED ON AN INTRA-LOOP
DENOISING MECHANISM**

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INTRODUCTION

1. Rationale of the dissertation

In recent years, medical imaging diagnosis has become an indispensable component of modern medicine, playing a key role in the early detection and treatment of dangerous diseases, especially cancer. According to World Health Organization (WHO) statistics for 2022, more than 2.3 million new breast cancer cases and approximately 685,000 deaths are recorded globally each year, with most deaths occurring in low- and middle-income countries lacking dedicated screening equipment [1]. In Vietnam, according to 2021 data from the Ministry of Health, more than 21,000 new breast cancer cases are diagnosed each year with a mortality rate exceeding 30%, clearly reflecting the reality of late detection due to limited access to diagnostic technology [2]. In this context, developing biomedical imaging techniques capable of early detection of small lesions, that are safe, affordable, and can be widely deployed has become an urgent requirement.

At present, the imaging modalities commonly used for breast pathology diagnosis all have certain limitations. Mammography, although the most widely used screening standard, has significantly reduced effectiveness for women under 50 with dense breast tissue, while ionizing radiation remains a safety concern for repeated examinations [3]. Magnetic resonance imaging (MRI) provides superior image quality but is very costly and requires long scanning times. Conventional ultrasound (B-mode) is safe and non-invasive but only provides qualitative information about tissue structure and cannot distinguish lesions smaller than 5 mm [4]. Given these limitations, Ultrasound Tomography (UST) has emerged as a promising approach, as it does not use ionizing radiation, has moderate equipment cost, and enables quantitative reconstruction of acoustic parameters (sound speed, attenuation coefficient, density) with high contrast [5]. In particular, by exploiting scattered signals from multiple directions, UST is capable of detecting tumors smaller than the wavelength — something conventional B-mode ultrasound cannot achieve [6]. The potential application of UST for early detection of abnormal masses in breast cancer diagnosis in women has also been confirmed by domestic studies [135].

The core problem of modern UST is image reconstruction from measured scattering data. Among the algorithms being studied, the Distorted Born Iterative Method (DBIM) is regarded as one of the most accurate methods thanks to its ability to handle strong scattering cases, overcoming the limitations of the first-order Born approximation [7]. However, DBIM still has two fundamental drawbacks: (i) very high computational complexity $O(N_t \cdot N_r \cdot N^2)$, which results in long reconstruction times; and (ii) high sensitivity to noise in the measured data, particularly under realistic conditions with low signal-to-noise ratio (SNR), leading to error accumulation across iterations and degrading the quality of the reconstructed image [8]. These are the two core issues that the research community has been striving to address for more than a decade.

Synthesizing and analyzing published studies directly related to improving the reconstruction quality of the DBIM algorithm in UST shows that existing approaches can be classified into the following main groups, based on the intervention point within the reconstruction pipeline:

Group 1 – Direct improvement of the DBIM algorithm to reduce computational complexity: Tran Quang Huy et al. (2014) [136], [139] proposed accelerated computation techniques to reduce the processing time of DBIM. However, these approaches focus solely on computational efficiency and have not addressed the noise-sensitivity issue of the DBIM algorithm, particularly the phenomenon of noise accumulation across iterations.

Group 2 – Compressive sensing and sparse sampling (intervention before DBIM): Tran Quang Huy et al. (2017) [131] proposed a Deterministic Compressive Sampling technique for UST, which reduces the amount of measurement data required while still ensuring reconstruction quality. Earlier, the same group (2016) [133] combined compressive sensing with a frequency-hopping technique for UST, and (2015) [137] proposed a reconstruction method based on L1-norm optimization for sound-contrast imaging. Candès and Wakin [20] laid the general theoretical foundation for compressive sensing. These methods intervene at the stage before the data is fed into DBIM, improving the quality of the input data but without any ability to control the noise that arises and accumulates during the iterative process.

Group 3 – Multi-frequency exploitation (combining data from multiple measurements): Tran Quang Huy et al. (2016) [18] demonstrated that combining data acquired at two different frequencies significantly improves UST image quality. Theu et al. (2022) [17] developed the MR-MF-DBIM (Multi-Resolution Multi-Frequency DBIM) technique for high-contrast scattering image reconstruction. Huy et al. (2020) [19] built an efficient multi-frequency pipeline for UST. Theu et al. (2021) [21] further extended this toward a multi-resolution direction. However, multi-frequency/multi-resolution methods considerably increase data-acquisition cost and system complexity, and still do not directly address noise accumulation within the DBIM iterations.

Group 4 – Spatial interpolation to enhance resolution (intervention after DBIM): A series of studies by Tran Quang Huy et al. proposed various interpolation techniques to improve UST image quality after DBIM has finished, including: nearest-neighbor interpolation [138], bicubic interpolation [134], bilinear interpolation applied to the DBIM approach [132], and more general interpolation techniques [142]. These interpolation techniques operate at the post-processing stage, merely "beautifying" the DBIM output image without improving solution quality during the iterative process, and therefore do not address the root cause of noise-induced quality degradation.

Group 5 – Optimization of measurement configuration and verification simulation: Tran Quang Huy and Tran Duc-Tan (2014) [140] investigated the influence of measurement configuration on reconstruction quality in UST. Tran Quang Huy et al. (2014) [141] performed simulation and experimental verification to generate standard UST datasets. This research direction intervenes at the hardware and measurement-system-layout level and is not directly related to the noise-handling mechanism within the reconstruction algorithm.

Group 6 – Deep-learning-based approaches: In recent years, deep learning has been applied to UST with promising results: Long et al. (2023) [22] used deep learning for UST with sparse sampling; Saba et al. (2022) [23] proposed Physics-Informed Neural Networks for diffraction tomography; Shi et al. (2022) [24] used deep learning to extract time-of-flight in bone UST. Architectures such as U-Net [47],

GAN [46], MoDL [52], deep cascade [51], and DnCNN [106] have also been applied to biomedical image restoration. However, these deep-learning methods are typically applied as post-processing after DBIM has finished (post-loop), while also requiring a large amount of labeled training data and high computational resources — conditions that are very difficult to satisfy in clinical UST settings, particularly at very low SNR [9], [10].

The above analysis reveals an important research gap: all existing approaches — including studies already published in Vietnam [131], [132], [133], [134], [135], [136], [137], [138], [139], [140], [141], [142], as well as recent international studies — intervene in the DBIM reconstruction pipeline at positions "outside" the iterative loop: either at the input pre-processing stage (Groups 2, 3, 5), the output post-processing stage (Groups 4, 6), or by improving computational efficiency without touching the noise-propagation mechanism (Group 1). To the author's knowledge, no study in the UST literature to date has integrated a denoising mechanism directly inside each iteration of the DBIM algorithm (intra-loop filtering), particularly by embedding lightweight machine-learning techniques within the loop to control noise accumulation throughout the iterative process. This is precisely the gap that the dissertation aims to address.

More specifically, the limitations of UST image reconstruction can be summarized into two issues. The first limitation concerns the sensitivity of DBIM to noise in the input data, especially when the number of measurements is limited ($N_t \cdot N_r < N^2$) — a common condition in practical UST systems. UST measurement data usually contain speckle noise (multiplicative noise) and additive white Gaussian noise [4]; when DBIM is applied directly to noisy data, errors accumulate across iterations and may cause the solution to diverge or yield a poor-quality image [8], [16]. Linear filters, median filters or frequency-domain techniques [33], [88], when applied to UST, are typically used only as pre- or post-processing steps independent of the DBIM iterative process, and therefore cannot control noise accumulation. A noise-handling mechanism integrated directly into each DBIM iteration is thus needed to halt error accumulation at an early stage.

The second limitation concerns deep-learning-based denoising methods (U-Net [47], DnCNN [106], GAN [46], deep

cascade [51], MoDL [52]) when applied to UST in high-noise environments: first, they require large numbers of labeled clean–noisy data pairs, which are extremely difficult to collect under clinical conditions, particularly at $\text{SNR} = 1\text{--}6$ dB; second, they demand large computational resources (GPUs, long training times), hindering deployment at resource-limited healthcare facilities [9], [10]; third, they are typically applied as post-processing after DBIM has finished [22], [24], and thus do not address noise accumulation within the iterations. Consequently, a lightweight denoising method is needed that does not depend on large-scale training data, can be integrated directly into the DBIM loop, and operates effectively even at very low SNR.

Therefore, researching and proposing ultrasound tomography (UST) image-restoration methods that integrate lightweight machine-learning techniques into each iteration of the DBIM algorithm (intra-loop filtering) — an approach that has not yet been explored in the UST literature — constitutes the main content presented in this dissertation. The fundamental difference and advancement of this dissertation compared with previous works are: (i) shifting the intervention point from "outside" (pre-/post-processing) to "inside" the DBIM iteration, enabling control of noise accumulation from an early stage; (ii) using non-parametric machine-learning techniques that require no training data (median filtering + K-means, KNN), overcoming the key limitation of deep-learning methods under conditions of scarce labeled data; and (iii) demonstrating the generality of the intra-loop DBIM filtering principle through successful application to both moderate-noise ($\text{SNR} \approx 26$ dB) and high-noise ($\text{SNR} = 1\text{--}6$ dB) regimes — conditions under which existing methods are almost inapplicable.

2. Objectives of the dissertation

General objective: To propose methods for improving the quality of ultrasound tomography (UST) image reconstruction based on the DBIM algorithm under noisy data conditions, by combining a physical model with lightweight, intra-loop-integrated machine-learning techniques that do not depend on large-scale training data and that ensure feasibility of deployment in practical systems.

Specific objectives: Based on an analysis of the limitations of the conventional DBIM algorithm and related published studies, the dissertation targets the following specific objectives:

First, to address the noise sensitivity of DBIM under insufficient-measurement conditions, the dissertation proposes integrating a 2D median filter combined with K-means clustering [29], [85] directly into each DBIM iteration (intra-loop filtering), controlling the accumulation of impulse noise across iterations and providing an unsupervised segmentation pipeline that requires no labeled data, suited to insufficient-measurement conditions ($N_t \cdot N_r < N^2$) [25].

Second, to address the large training-data requirement and high computational cost of deep-learning methods in high-noise environments, the dissertation proposes a KNN-based denoising method [30], [103] integrated within the DBIM loop, which exploits KNN as an adaptive non-parametric filter, requires no training data and operates effectively at very low SNR (1–6 dB), where supervised learning methods are almost inapplicable [26].

Third, to verify the generality of the intra-loop DBIM filtering principle through a consistent evaluation of the two proposed methods on simulated and experimental datasets across different SNR levels, thereby confirming that this is a general design principle that can be extended to other types of filters.

3. Research object and scope

The dissertation focuses on researching and studying a number of objects related to the problem of improving ultrasound tomography (UST) image quality, including:

Methods and models for UST image reconstruction, with a focus on the Distorted Born Iterative Method (DBIM) and its variants [7], [16], [32], [33], [136], [139].

Types of noise in UST systems, including speckle noise (multiplicative noise), additive white Gaussian noise, and noise arising during the inverse-problem-solving process [4], [8].

Lightweight image-processing and machine-learning techniques applied to denoising, including median filtering, K-means clustering [29], [85], [86], and the K-Nearest Neighbors (KNN) algorithm [30], [100], [103].

Metrics for evaluating reconstruction image quality (NE, NERR, CNR, boundary error) and simulated/experimental datasets used to verify the proposed methods [141].

4. Scope of the dissertation

Studying an intra-loop DBIM denoising method based on median filtering combined with K-means clustering to improve reconstruction quality under moderate-noise and insufficient-measurement conditions.

Studying an intra-loop DBIM denoising method based on the KNN algorithm for high-noise environments ($\text{SNR} = 1\text{--}6\text{ dB}$) without requiring training data.

The proposed methods are designed and evaluated in a two-dimensional space, using both simulated and experimental data.

The dissertation does not go deeply into deep-learning methods that require large-scale training data, does not consider three-dimensional models, and does not include the hardware design of the UST system.

The specific application of reconstructed UST images to particular clinical pathologies lies outside the scope of this dissertation.

5. Research methodology

Theoretical research: Synthesizing and analyzing studies related to the inverse-scattering problem, ultrasound tomography (UST) techniques, and denoising methods published domestically and internationally [7], [8], [16]–[24], [131]–[142]. Based on an analysis of the remaining issues in current approaches — particularly the gap regarding an intra-loop DBIM noise-intervention mechanism — proposing effective denoising methods that are integrated directly into the DBIM loop in order to overcome the identified limitations.

Experimental research: The proposed methods are implemented, simulated and evaluated using quantitative metrics (NE, NERR, CNR, boundary error) combined with visual assessment, on simulated phantom images and UST datasets at various SNR levels (from 1–6 dB to about 26 dB); the results are compared with conventional DBIM and recent improved methods such as DF-DBIM [18], MR-MF-DBIM [17], [21], compressive sensing [131], [133], interpolation [132], [134], [138] and deep-learning models for UST [22]–[24].

6. Contributions of the dissertation

To improve UST image reconstruction under noisy data, the dissertation makes two main contributions, both belonging to a new design paradigm not previously reported in the UST literature — "intra-loop filtering":

Contribution 1: proposing a method that integrates a 2D median filter combined with K-means clustering directly into each iteration of DBIM. Unlike previously published pre-processing approaches based on compressive sensing [131], [133], [137] or post-processing based on interpolation [132], [134], [138], [142], the method controls noise accumulation during the iterative process itself and provides an unsupervised segmentation pipeline requiring no labeled data. It achieves NERR = 86.39% at $N_t = N_r = 10$, clearly outperforming DF-DBIM (57.5%) [18], and has been published in work [CT1] (reference [25]).

Contribution 2: proposing a denoising method based on the K-Nearest Neighbors (KNN) algorithm integrated within the DBIM loop for high-noise environments ($\text{SNR} = 1\text{--}6$ dB). This is the first time in the UST literature that a non-parametric machine-learning technique has been embedded inside each DBIM iteration rather than used merely as a post-processing classifier. The method requires no training data, is many times lighter than deep-learning methods, and suits very low SNR conditions — where post-loop deep-learning methods [22], [24] cannot be applied. It has been published in work [CT3] (reference [26]). In addition, the dissertation verifies the generality of the intra-loop DBIM filtering principle: both median filtering (moderate SNR) and KNN (low SNR) yield significant improvement when embedded inside the DBIM loop.

7. Structure of the dissertation

Besides the introduction and the conclusion, the dissertation comprises three content chapters, a list of the author's publications and a list of references.

Chapter 1 presents an overview and the theoretical foundation of ultrasound tomography (UST): the research context, operating principles and classification of UST techniques, and key theoretical foundations (wave equation, Green's function, Born/Rytov approximations, BIM/DBIM algorithms); it analyzes the limitations of current methods and clarifies the research gap.

Chapters 2 and 3 present the main contributions. Chapter 2 proposes integrating a median filter combined with K-means clustering into the DBIM loop, targeting moderate-noise conditions and the insufficient-measurement problem. Chapter 3 proposes a KNN-based denoising method integrated within the DBIM loop for high-noise environments ($\text{SNR} = 1\text{--}6$ dB), improving stability and image quality directly during the iterative process.

The conclusion presents the main contributions of the dissertation and future research directions.

CHAPTER 1. OVERVIEW AND THEORETICAL FOUNDATION OF ULTRASOUND TOMOGRAPHY (UST) IMAGING TECHNIQUES

1.1. Problem statement and research context

Ultrasound is one of the most widely used medical imaging techniques thanks to its advantages of not using ionizing radiation, low cost, and real-time operation. Among ultrasound techniques, B-mode ultrasound is widely used clinically; however, this method mainly provides qualitative information and depends heavily on the operator's experience.

To overcome these limitations, Ultrasound Tomography (UST) has been developed as an advanced approach that enables quantitative reconstruction of the medium, such as the distribution of sound speed or tissue density. As a result, UST has the potential to improve diagnostic accuracy, particularly in detecting small lesions.

In ultrasound tomography, transducers are arranged around the object and operate alternately in transmit and receive modes. As the ultrasound wave propagates through an inhomogeneous medium, it is scattered in many directions. These scattered signals are acquired from multiple angles, forming the input dataset for the image-reconstruction problem.

The image-reconstruction process is built on solving an inverse problem, in which the physical parameters of the medium are inferred from the measured data. This is a complex problem due to its non-linearity and instability.

Quantitative ultrasound techniques (in this case, ultrasound tomography) are known to provide more useful/quantitative information than B-mode imaging. There are two main research directions for this

technique: Ray-based ultrasound tomography and Scattering-based ultrasound tomography.

1.2. Ray-based ultrasound tomography:

The ray-based approach is one in which the propagation of the ultrasound wave is approximated as rays traveling along straight lines through the medium.

The ray-based approach is suitable for problems with low contrast and large structures; however, it is not accurate enough for cases requiring the reconstruction of fine details.

The ray-based approach assumes that waves travel in straight lines and ignores scattering phenomena, giving it the advantage of simplicity and fast computation. However, because it does not fully account for the wave nature of the signal, this method has low accuracy and is not suitable for problems requiring high resolution. This method ignores scattering and diffraction phenomena, thereby significantly simplifying the physical model.

1.3. Scattering-based approach

The scattering-based approach describes the propagation of the ultrasound wave in an inhomogeneous medium, in which the wave not only travels in a straight line but is also scattered in many directions due to variations in physical parameters such as sound speed or density.

Unlike the ray-based approach, this method fully accounts for the wave nature of the signal, thereby allowing image reconstruction with higher accuracy. The scattering-based approach is sensitive to noise because the received signal is a composite of scattering contributions from the entire medium, so noise at any location affects the entire dataset.

There are two research directions in ultrasound tomography techniques based on inverse-scattering theory: ultrasound tomography using the first-order Born approximation, and ultrasound tomography using the first-order Rytov approximation. The first-order Born approximation is preferred by researchers because: the condition for the first-order Born approximation to be valid is that the scattered pressure is much smaller than the pressure of the incident wave within the imaged object. Unlike the Born approximation, the Rytov approximation is not limited by the size of the scattering object, and therefore this method is often valid over a wide range of imaging

objects. However, inversion using the Rytov approximation often encounters the phase-wrapping problem. From the above analysis, when the phase condition is satisfied, the ultrasound tomography technique using the first-order Born approximation operates fairly stably and provides sufficiently good image-restoration quality. Therefore, in this dissertation, the author selects the ultrasound tomography technique using the first-order Born approximation to continue researching and developing this method. $|\Delta\phi| < \pi$

1.4. Noise in ultrasound images includes

In ultrasound images, noise is an unavoidable factor that significantly affects image quality as well as diagnostic accuracy. Common types of noise include:

- (i) Impulse noise, typically salt-and-pepper noise;
- (ii) Additive noise, usually modeled as additive white Gaussian noise (AWGN);
- (iii) Multiplicative noise, typically speckle noise.

Denoising in medical images in general, and ultrasound images in particular, is a major challenge, as it requires both removing noise and preserving important image features, especially edges. An effective denoising method must ensure a balance between noise reduction and detail preservation. In practice, denoising methods are usually built on filtering techniques. Among the noise types mentioned above, speckle noise is the dominant component and has the greatest impact on ultrasound image quality. This noise arises from the interference of ultrasound waves reflected from different tissue structures within the body, and typically appears as random granular patterns in the image.

Being multiplicative noise, speckle has a more complex nature than additive noise, making it more difficult to process. Speckle degrades image contrast and resolution, obscures important details, and thereby directly affects diagnostic accuracy. In addition, it also reduces the effectiveness of subsequent image-processing tasks such as segmentation.

Therefore, speckle reduction is an important pre-processing step that plays a decisive role in improving ultrasound image quality and the effectiveness of subsequent processing methods.

1.7. Conclusion of Chapter 1

Chapter 1 has presented an overview of medical imaging

methods, with a particular focus on ultrasound tomography. Traditional techniques such as B-mode ultrasound and computed tomography (CT) were analyzed to clarify the advantages and limitations of each method. Among them, ultrasound tomography stands out for its ability to provide quantitative information and its potential for diagnostic applications while still ensuring safety.

CHAPTER 2. IMPROVING ULTRASOUND TOMOGRAPHY IMAGE RECONSTRUCTION USING A FILTERING METHOD COMBINED WITH A MACHINE-LEARNING TECHNIQUE

2.1. Introduction

The author proposes a median filtering technique to reduce noise without affecting the structural integrity of the image. The procedure consists of acquiring ultrasound tomography data, reconstructing it with DBIM, and applying a median filter to the reconstructed image; effectiveness is evaluated quantitatively using the normalized error. Machine-learning solutions for enhancing ultrasound image quality [109]-[113] typically rely on complex computations; by integrating median filtering into DBIM together with lightweight machine learning, this study aims at a comprehensive solution to noise in UST, significantly reducing noise while preserving the essential structural details of the image.

In addition, K-means clustering — a simple machine-learning method — is used to automatically segment the reconstructed image into object, background and noise regions based on pixel intensity values, so that pixels within a cluster are more similar to each other than to pixels in other clusters. The results show that K-means effectively distinguishes the regions in images obtained by the proposed method, highlighting the potential of combining median filtering with K-means clustering to improve segmentation and image restoration in ultrasound tomography.

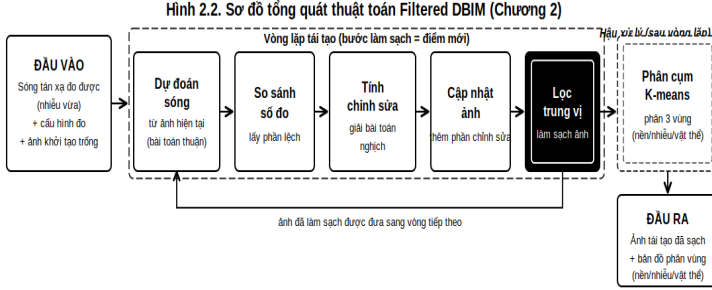


Figure 2.2. Diagram of the Filtered DBIM algorithm – the median filter is embedded at Step 6 of each DBIM iteration

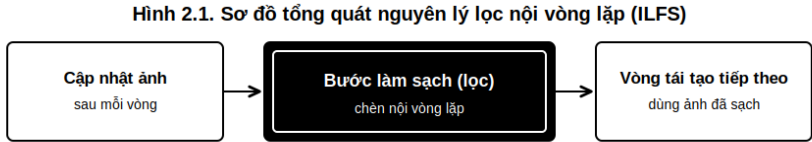


Figure 2.1. Diagram of the intra-loop filtering principle (ILFS) – the median filter is placed at Step 6 of DBIM, immediately after the image update and before the next iteration

2.2. Simulation and results

The simulation parameters are: incident frequency $f = 1$ MHz (satisfying the Born approximation condition); the numbers of transmitters N_t and receivers N_r (which determine the number of measurements $N_t \times N_r$) calibrated for each scenario; $N_{sum} = 5$ iterations; the region of interest divided into $N = 12$ pixels per axis ($N^2 = 144$ unknowns); a 10 mm scattering-region diameter; a 10% sound-speed contrast; and a 60 mm distance from the transmitters and receivers to the object center. To simulate realistic conditions, zero-mean additive Gaussian noise with a standard deviation of 5% of the maximum measured-signal amplitude was added to the scattered-field data, reflecting electronic noise, amplifier-induced variations and environmental noise in practical ultrasound systems.

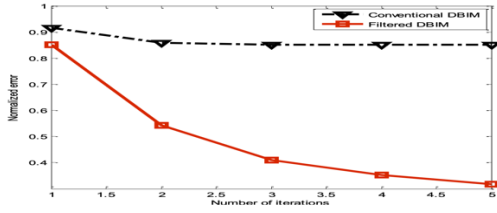


Figure 2.6. Reconstructed images over 5 iterations: conventional DBIM (top row) and Filtered DBIM (bottom row) at $N_t = N_r = 6$

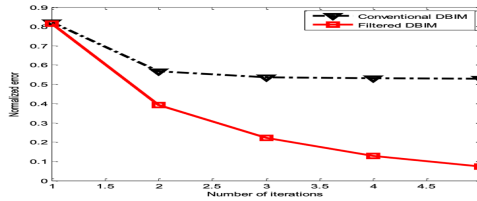


Figure 2.8. Reconstructed images over 5 iterations: conventional DBIM and Filtered DBIM at $N_t = N_r = 10$ (iteration 5: DBIM diverges, $NERR = 86.39\%$)

To illustrate the effectiveness of the filtered DBIM method under conditions where the number of measurements is fewer than the number of unknowns, we performed a comparative analysis of the normalized error between the filtered DBIM technique and the dual-frequency DBIM (DF-DBIM) [19], [20], [21], [22], as presented in the Table. The filtered DBIM method exhibits a significantly superior convergence rate compared with the DF-DBIM method, as evidenced by the reduced normalized error observed at each iteration. Notably, from the very first iteration, the filtered DBIM technique clearly shows a superior convergence rate compared with DF-DBIM. This difference underscores the superior performance of the filtered DBIM method, particularly when handling a limited number of measurements relative to the number of unknowns.

It should be noted that the current study uses simulated data generated under controlled conditions, which allows precise quantification of reconstruction errors and direct comparison with ideal targets; application to real datasets will be addressed in subsequent studies.

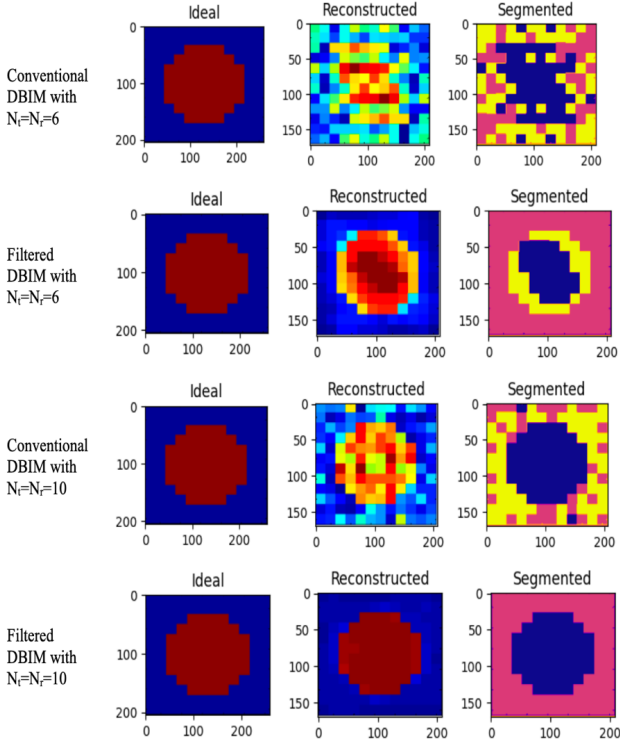


Figure 2.11. Ground truth, reconstructed image, and K-means segmentation ($K=3$): Filtered DBIM yields sharp segmentation, closely matching the ground truth

The proposed method operates according to the Intra-Loop Filter Stabilization (ILFS) principle: a 2D median filter is embedded directly at Step 6 of each DBIM iteration — immediately after updating the image and before computing the Jacobian for the next iteration. The fundamental difference compared with previous methods is that the intervention mechanism lies inside the loop, rather than in pre-processing or post-processing. This makes it possible to halt the error-amplification chain from an early stage, rather than merely "beautifying" the output image after noise has already accumulated.

Experimental results with $N_{\text{sum}} = 5$ iterations, 5% AWGN ($\text{SNR} \approx 26$ dB), and three scenarios $N_t = N_r \in \{6, 10, 12\}$ show that: at $N_t = N_r = 10$, conventional DBIM diverges at iteration 5 (NE increasing from 0.32 to 0.53), whereas Filtered DBIM achieves $\text{NE} = 0.0721$, corresponding to $\text{NERR} = 86.39\%$ — outperforming DF-DBIM (57.5%). The Monte Carlo variance decreases from 8.3% (conventional DBIM) to 1.2% (Filtered DBIM), demonstrating the high stability required for clinical applications.

Advantages: (i) NE reduced by 45–86% depending on the scenario; prevents divergence under severely insufficient-measurement conditions. (ii) Additional computational cost is under 0.01% per iteration — with no impact on overall speed. (iii) K-means with $K=3$ provides automatic three-region segmentation (object/background/noise) without requiring labeled training data. (iv) No change to the UST system hardware.

Limitations: (i) Median filtering is suited to impulse noise; it is less effective when SNR is very low (1–6 dB), where Gaussian noise dominates. (ii) A fixed filter window of $k=1$ may blur fine boundaries in complex phantoms. (iii) The results are primarily verified on simple 2D phantoms; they have not yet been verified on real clinical data. These limitations are the motivation for developing the KNN-filtered DBIM method in Chapter 3, targeting low-SNR environments.

2.3 Conclusion of Chapter 2

This chapter has proposed a filtered image-reconstruction framework for UST by embedding median filtering into the iterative DBIM process, followed by K-means clustering for segmentation. Simulation results show that the proposed method significantly reduces the normalized error compared with both conventional DBIM and DF-DBIM across different configurations; the reconstructions closely approximate the ideal object function, with sharper boundaries and less noise, and K-means clearly delineates object, background and noise regions, improving the interpretability of the reconstructed images.

CHAPTER 3. IMPROVING ULTRASOUND TOMOGRAPHY IMAGE RECONSTRUCTION USING A FILTERING METHOD COMBINED WITH A MACHINE-LEARNING TECHNIQUE

This chapter presents a novel integration: an adaptive K-Nearest Neighbors (KNN) denoising filter applied at each iterative update of DBIM — which, to our knowledge, has not previously been reported in ultrasound tomography. This approach enhances noise suppression without affecting structural resolution and addresses the limitations of conventional regularization methods (e.g., Tikhonov regularization) in high-noise scenarios.

3.1 K-nearest neighbors (KNN) for denoising in DBIM

The main advantages of using KNN in DBIM are: (a) preservation of structural detail — unlike traditional smoothing filters, KNN does not blur edges or fine features; (b) adaptability to non-linear data, since KNN relies on similarity measures rather than fixed transformations; (c) computational efficiency — no pre-training is needed, making it a lightweight solution that is easy to integrate into iterative DBIM.

The overall workflow of the proposed KNN-filtered DBIM is illustrated in Figure 3.3: DBIM is initialized from the measured scattered-field data (with Gaussian noise added to simulate real measurement uncertainty); a KNN-based denoising step suppresses high-frequency noise components while preserving structural information; the denoised data are used to update the contrast function; and these steps are repeated until convergence, producing the final reconstructed sound-speed distribution.

KNN denoising is applied within DBIM as follows: (i) noise identification — at each iteration the reconstructed field is affected by noise that can cause numerical instability; (ii) local neighbor selection — for each pixel, a set of K nearest-neighbor pixels is identified by Euclidean distance; (iii) weighted averaging — the target pixel is replaced with the weighted average of its K nearest neighbors, smoothing noise while preserving high-contrast features; (iv) iterative refinement — the denoised image is fed into the next DBIM iteration, enhancing stability and accelerating convergence.

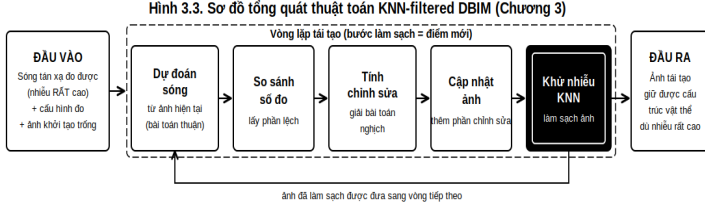


Figure 3.3. Diagram of the KNN-filtered DBIM algorithm – an intensity-based KNN filter is embedded at Step 6 of each DBIM iteration, replacing the median filter

The KNN-filtered DBIM method applies intensity-based KNN denoising (in intensity space, not spatial position) at Step 6 of each DBIM iteration. For each pixel x_i , the K nearest neighbors by intensity value are found and the pixel is replaced by their average: $\hat{x}_i = (1/K) \cdot \sum_{j \in NK(i)} x_j$. Variance-reduction analysis: $\text{Var}(\hat{x}_i) = \sigma^2 n / K$ — with $K=5$, the variance is reduced 5-fold, equivalent to an SNR gain of 7 dB. An image with SNR = 1 dB, after KNN filtering, becomes equivalent to SNR $\approx$ 8 dB, sufficient for DBIM to converge stably.

3.2 Results and discussion

Experiments were conducted on a cylindrical phantom of radius 7.3 mm, $f = 0.5$ MHz, a 12×12 grid, $N_t = N_r = 12$, at three SNR levels = {6, 3, 1} dB. First-iteration results: NERR reached 49.5% (SNR=6 dB), 49.0% (SNR=3 dB), and 57.2% (SNR=1 dB) — an increasing trend as SNR decreases, consistent with theory: KNN is most effective when noise is strongest. Over 3 iterations, KNN-filtered DBIM consistently maintains a lower NE than both conventional DBIM and Median-filtered DBIM at every SNR level.

The simulated target is an infinite circular cylinder with a 10% sound-speed contrast. The transmitters are equally spaced along a circle surrounding the object; for each transmitter, 12 receivers placed on the opposite side of the circle capture the scattered signals.

Integrating KNN filtering into DBIM provides a light and flexible improvement to a well-established reconstruction algorithm, enabling deployment in clinical or real-time applications, point-of-care systems or low-cost platforms where computational resources and data are

limited, while preserving the physical interpretability of DBIM and improving its robustness against measurement noise.

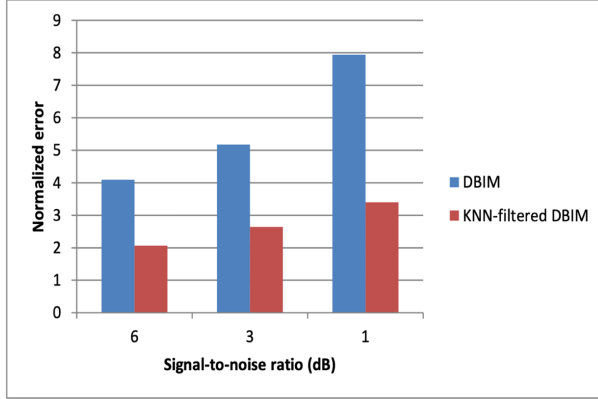


Figure 3.5. Normalized error NE after the first iteration at SNR = 6, 3, and 1 dB (NERR: 49.5%; 49.0%; 57.2%)

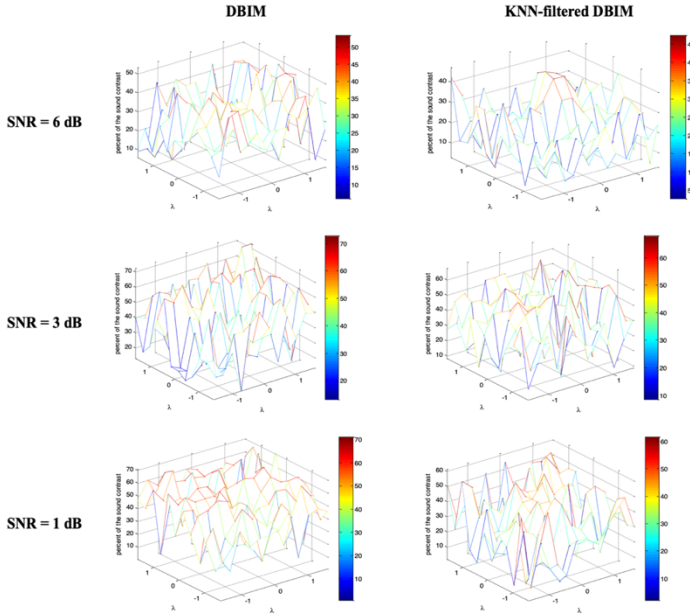


Figure 3.6. Reconstructed images after the first iteration – conventional DBIM (top row) and KNN-filtered DBIM (bottom row) at SNR = 6, 3, 1 dB

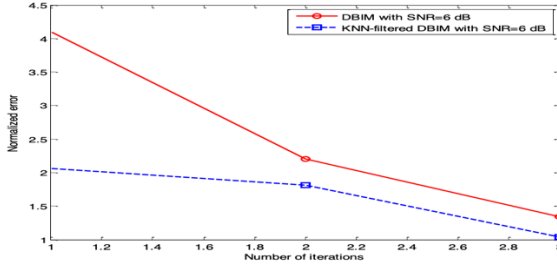


Figure 3.7. Evolution of NE over 3 iterations at SNR = 6 dB – KNN-filtered DBIM maintains an NE about 50% lower at every iteration

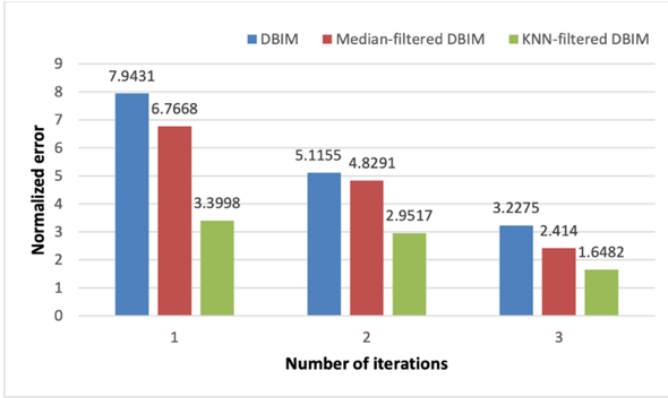


Figure 3.10. Comparison of NE over 3 iterations of DBIM, Median-filtered DBIM, and KNN-filtered DBIM at SNR = 1 dB

Advantages: (i) NERR increases monotonically as SNR decreases – highest effectiveness precisely under the most difficult conditions. (ii) Requires no training data; operates directly on each reconstructed image. (iii) Many times lighter than deep learning: computational cost of $O(N^4) \approx 8\text{--}10\%$ per iteration, suitable for deployment on devices without a GPU. (iv) Verifies the generality of the ILFS principle: both Median (moderate SNR) and KNN (low

SNR) provide significant improvement, suggesting that ILFS is an extensible design principle applicable to many other filters.

Limitations and future directions: (i) $O(N^4)$ cost is higher than median filtering; parallel GPU processing is needed when $N \geq 32$. (ii) Effectiveness decreases for multi-object phantoms due to more complex intensity distributions. (iii) Not yet verified on in vivo clinical data. Priority future directions: (1) Verification on multi-layer physical phantoms and clinical UST data; (2) Extension to 3D reconstruction with GPU parallelization; (3) Investigation of other ILFS filters (bilateral filter, non-local means) to extend the family of methods.

3.3. Conclusion

This chapter has integrated a KNN-based machine-learning denoising method into DBIM to enhance reconstruction stability and reduce noise sensitivity. Unlike Tikhonov regularization, which does not reduce noise effectively, the proposed method leverages local neighborhood relationships to perform adaptive denoising. Simulation results for sound-speed contrast reconstruction confirm that the proposed method outperforms conventional DBIM in noise resilience, convergence speed and overall image quality, while preserving important structural details.

CONCLUSION

The dissertation makes three novel contributions that can be confirmed by quantitative evidence. The first novel point concerns the principle: integrating a non-parametric, non-linear filter inside the DBIM loop at the image-update step. All previous studies either used only mathematical regularization without intervening in the intermediate image, or filtered after the loop had finished. Placing the filter at the correct position within the loop — not after it — is the fundamental difference that produces the observed cumulative effect.

The second novel point concerns the pipeline: combining Filtered DBIM with unsupervised K-means, creating a complete pipeline from raw scattering data to a semantically labeled three-region image, fully automatic, requiring no training data and no expert image reader for the segmentation step.[85][86]

The third novel point concerns the generality of the evidence: two results chapters using two different filters (Median and KNN), across two different SNR ranges (26 dB and 1–6 dB), both show that the intra-loop filtering principle operates consistently, suggesting that this is a general design principle independent of the specific filter chosen.

Before this dissertation, no method in the UST literature simultaneously satisfied all four criteria: intra-loop non-linear filtering instead of post-processing, requiring no labeled training data whatsoever, no hardware modification, and better results than the best multi-frequency method in the same class. Both works [CT1] and [CT3] simultaneously satisfy these four criteria.[25][26]

LIST OF THE PUBLICATIONS RELATED TO THE DISSERTATION

1. **Nguyen Quang-Huy** and **Nguyen Truong Thang** (2025), “*Tomographic Image Reconstruction Enhancement through Median Filtering and K-means Clustering*”, International Journal of Electrical and Computer Engineering (IJECE) (SCOPUS), Vol.15, No.5, October 2025, pp.4395 ~ 4408. ISSN: 2088 – 8708. <http://doi.org/10.11591/ijece.v15i5.pp4395-4408>.
2. **Nguyen Quang-Huy** and **Nguyen Truong Thang** (2025), “*Nâng cao chất lượng ảnh chụp siêu âm cắt lớp bằng cách ứng dụng kỹ thuật nội suy*”, **Hội thảo quốc gia “Một số vấn đề chọn lọc của Công nghệ Thông tin và Truyền thông” lần thứ XXVIII (VNICT 2025), 15/11/2025**
3. **Nguyen Quang-Huy** and **Nguyen Truong Thang** (2026), “*Distorted born iterative method reconstruction in high-noise environments using KNN-based machine learning denoising*”, Telecommunication, Computing, Electronics and Control (TELKOMNIKA) (SCOPUS), Vol.24, No.1, February 2026, pp.206 ~ 218 . ISSN: 1693 – 6930. DOI: <http://doi.org/10.12928/telkomnika.v24i1.27401>