International Journal of Environmental Sciences
ISSN: 2229-7359
Vol. 11 No. 18s, 2025
https://www.theaspd.com/ijes.php

Tomographic Reconstruction Via Fourier And Wavelet Transformations: Enhancing Signal Analysis Techniques

P. Maheswari[1*], Mr. Mohammad Haadi Bhat[2], Anjali Verma[3]

[1]Assistant Professor, Department of Mathematics University: Mepco Schlenk Engineering College, Sivakasi, Tamil Nadu Email ID: maheswari23061993@gmail.com
[2]Assistant Professor, Chandigarh Group of Colleges Jhanjeri, Mohali - 140307, Punjab, India Department of Sciences, Chandigarh School of Business, Email ID: bhathaadi6@gmail.com
[3]Assistant Professor, Department of research and incubation, Rayat Bahra University, Mohali (140104), Punjab (India)
Email ID: anjalivermma@gmail.com

Abstract
Tomographic reconstruction is essential in medical and industrial imaging, which reconstructs cross-sectional structures from projection data. Conventional reconstruction algorithms, primarily relying on Fourier transforms, effectively reconstruct global frequency patterns, but may introduce artifacts in the case of low-dose or limited-angle CT. The wavelet transformations are useful for the preservation of the localized details but fail in coherency in broader structures and are noisy in smooth areas. In this work, a new Fourier-wavelet model is proposed as the integration of the Fourier and wavelet transformations that provide high-quality tomographic reconstructions. The hybrid approach of Fourier's global frequency capture with wavelet's spatial localization reduces artifacts, improves edge preservation, and optimizes structural preservation, especially in situations with limited projection. Numerical analysis shows that the hybrid model is 40% more accurate in reconstruction error than Fourier-only and 30% more accurate than wavelet-only methods. This model offers a feasible and efficient solution for image reconstruction in the low-data and noisy environment and can be used in the low-dose CT and industrial imaging. These results evidence the effectiveness of the hybrid approach to offer artifact-minimal reconstructions, which is a major advancement toward enhancing the accuracy and time efficiency of tomographic imaging.

Keywords: *Tomographic reconstruction, Fourier transform, wavelet transform, hybrid model, limited-angle tomography, low-dose CT, image fidelity, artifact reduction.*

INTRODUCTION

Tomography or computed tomography, an essential modality in medical diagnosis and industrial testing, entails the formation of cross-sectional images from projection data acquired at different orientations (Kak & Slaney, 2001). The key to tomographic reconstruction is the preservation of structural features and the reduction of artifacts that is sometimes difficult when there is a small amount of projection data or low-quality signal (Shepp & Logan, 1974). Fourier transform methods have been used traditionally in this field because they are efficient in processing global frequency information and can reconstruct gross structural features of an object. However, Fourier-based methods are not very localized in space and hence suffer from blurring and streaking especially in high frequencies or when data is missing (Bracewell & Kahn, 1966).

As a consequence of these limitations, new wavelet transformations have been developed as an additional or supplementary method of tomographic reconstruction (Mallat, 1989; Daubechies, 1992). Multi-resolution analysis is achieved through wavelets, which also offer localization of the frequency and spatial information, hence improving on edge preservation and detail accuracy. This property of wavelets has made them useful in dealing with high frequency localized features, and helped to overcome some of the spatial localization problems associated with Fourier based techniques (Bhatia et al., 1996). However, wavelet methods also have some disadvantages: they add noise to smoother areas because these methods are very sensitive to localized changes; this is why they are not very efficient when reconstructing the global structure (Vetterli et al., 2014). As such, although Fourier and wavelet transforms are both advantageous for tomographic reconstruction in their own right, each of them fails to provide the best compromise between global and local features preservation, particularly in the case of limited-angle or low-quality data.

The tomographic reconstruction problem becomes more challenging in cases where full projection data is not obtained. Incomplete data, where projection data is acquired over a small range of angles, is often used in clinical practice to minimize the radiation dose to the patient and in industrial applications where access to a large number of angles is impossible (Kuchment, 2013). This leads to undersampled projections, incomplete frequency information, which in turn magnifies artifacts and reconstruction errors in conventional approaches (Chen et al., 2008). The authors of prior works on compressed sensing (Candes et al., 2006) and dictionary learning-based reconstruction (Xu et al., 2012) have proposed techniques to reconstruct the high-quality image from sparse data. However, these approaches may involve high optimization procedures and may not be stable and may demand high computational time in real-time imaging.

In this regard, the present work proposes a combined Fourier-wavelet transform to take advantage of both transformations for efficient tomographic reconstruction from sparse data. The Fourier transform is used to obtain the global frequency structures of the image while the wavelet transform is used to enhance the local details of the image and the hybrid model provides a balanced reconstruction free of artifacts and with clear edges. This model directly targets the problems identified in the Fourier-based reconstructions, including streak artifacts and edge blurring and the noise amplification problems that are characteristic of wavelet-only methods (Mallat, 1989; Rivenson et al., 2018). This is because the hybrid approach reduces the reconstruction error in both low-dose and limited-angle cases, which is in line with current multiscale and hybrid imaging strategies (Bhatia et al., 1996; Sidky & Pan, 2008).

The importance of the work presented in this paper is in the fact that the proposed approach can be used in a range of medical and industrial imaging fields. Also in medical imaging, minimizing the radiation dose while maintaining the image quality is of paramount significance to the overall patient care (Xu et al., 2012). The hybrid Fourier-wavelet model provides a solution to this problem by giving the maximum reconstruction quality from sparse or low-dose data, which is required for low-dose CT scans or real-time imaging during surgeries. Moreover, this model may be useful in industrial applications where imaging conditions restrict the range of data acquisition directions, as it can produce accurate reconstructions from fewer projection data with less artifacts (Kuchment, 2013). Compared to prior methods, which may need much time for iterative optimization or high computational power, our hybrid model provides a relatively simple approach to trade off the computational cost for the reconstruction quality for real-time applications.

The following are the objectives of this research.

1. Construct a composite Fourier-wavelet methodology that utilizes both Fourier transforms scheme that facilitates the global frequency acquisition and conforms to the wavelets scheme that enables the localized analysis to improve the pathbreaking tomographic reconstructions.
2. Test the hybrid model under limited-angle conditions and compare its reconstruction accuracy, artifact suppression and edge preservation with Fourier-only and wavelet-only methods (Shepp & Logan, 1974; Chen et al., 2008).
3. Examine the potential of the hybrid approach in situations where data is limited, including low-dose CT and industrial imaging, to provide a high-quality, low-data tomographic imaging system

LITERATURE REVIEW

Tomographic reconstruction is a critical component of various disciplines, including medical imaging and industrial inspection, for reconstructing the 3D object from 2D projection data. The conventional approach of reconstructing the object from the Fourier coefficients was to use the inverse Fourier transform, which, although good for reconstructing the global structure of the object, has problems with spatial localization; it produces artifacts and loses details when data is sparse or noisy (Kak & Slaney, 2001; Shepp & Logan, 1974). Fourier transformations are global in nature, providing frequency information over the data set as a whole and with the disadvantage that it is difficult accurately to determine the position of localized structural features. This limitation can be especially critical in limited-angle tomography, in which only a subset of the projection angles is available, which leads to under sampled data and image artifacts (Bracewell & Kahn, 1966).

To overcome these limitations wavelet-based methods have been developed which offer multi resolution analysis and can analyze the localized features preserving the structural characteristics at different scales (Mallat 1989, Daubechies 1992). Wavelet transformations are also good in spatial and frequency localization; they are good in preserving edge details and bad in generating artifacts in high-frequency areas (Bhatia, Karl, & Willsky, 1996).

Wavelets assess data at different levels of resolution and preserve the high-frequency components as well as capture structural features in the high-scale images. This characteristic has been advantageous in medical imaging since edges as well as structures must be clear for diagnosis (Vetterli, Kovačević, & Goyal, 2014). However, wavelet-based methods can enhance detail preservation but at the same time add noise in smooth regions because of their high sensitivity to local changes, thus giving a trade-off between noise and detail retention (Mallat, 1989).
There has been a new trend in tomographic reconstruction where different transformation methods are combined in hybrid and data-sparse methods. One of the advancements is the combination of compressed sensing and dictionary learning that allows to reconstruct the signal with high quality from the undersampled data in the case of sparse signal representation (Candes, Romberg, & Tao, 2006; Xu et al., 2012). CS methods reconstruct signals from a subset of frequency information, and are useful in image reconstruction, especially in cases of limited angle projections because of their ability to focus on sparsity (Chen, Tang, & Leng, 2008). Dictionary learning based methods on the other hand has shown better results in low dose CT image by learning the adaptive dictionaries that are more efficient in retaining the details and suppressing the noise which is important in real time medical imaging as pointed by Elad & Aharon, 2006. However, these techniques are effective but they involve complicated optimization processes and their computational cost may not be feasible for real time or large-scale imaging applications (Rivenson et al., 2018).
There are still some issues in achieving the balanced reconstruction quality under the practical conditions by using the compressed sensing and dictionary-based approaches. Kuchment (2013) and Rivenson et al. (2018) have demonstrated that the use of hybrid and deep learning techniques enhance the reconstruction quality but their applicability to different imaging environments such as varying noise levels, number of projection angles or resolution requirements is still an issue. Other conventional techniques such as Fourier or wavelet only methods are also inadequate as they either do not have spatial resolution or they lose global detail due to the inherent localized nature (Kak & Slaney, 2001; Mallat, 1989). Moreover, the developed hybrid models often depend on iterative optimization, which can be inapplicable in cases that need fast image analysis, for instance, intraoperative imaging or industrial inspection.
To fill these gaps, our research introduces a hybrid Fourier-wavelet model that is capable of providing both global and localized reconstruction requirements efficiently. This model relies on the Fourier transform for the structural information of the image while using the wavelet transform for the high frequency, localized information thus gives a more artifact-free and structurally accurate reconstruction. As opposed to the previously described hybrid models, which may require multiple iterations (Sidky & Pan, 2008; Bhatia et al., 1996), the Fourier-wavelet approach used in this study is relatively simple and thus suitable for real-time or large-scale imaging. Thus, the combined use of the proposed techniques in the hybrid approach avoids the drawbacks observed in previous investigations, such as streak artifacts and noise enhancement, without involving complex calculations.
The value of this work is that it can be useful for limited-angle and low-dose imaging, which often causes difficulties in using traditional approaches. Compared to compressed sensing or dictionary learning, the hybrid Fourier-wavelet model provides a less complex solution with virtually no additional computation cost but with high reconstruction quality. In addition, flexibility in terms of data availability is a plus to the model given the current trends in imaging environments including low dose CT scans and industrial tomography where image quality and speed are paramount (Xu et al., 2012; Chen et al., 2008). This research therefore adds to the ongoing development of tomographic reconstruction by providing a balanced, cost-effective model that can overcome the challenges of the basic approaches in the different imaging scenarios.

METHODOLOGY

This methodology describes a tomographic reconstruction approach that uses Fourier transforms for global frequency and wavelet for local spatial details. This fusion affords higher resolution and reduction of artifacts particularly when information is scarce or noisy. It combines Fourier and wavelet transformations in an iterative approach and provides accurate and reliable imaging for sophisticated uses.

Fourier Transform for Global Frequency Reconstruction

International Journal of Environmental Sciences
ISSN: 2229-7359
Vol. 11 No. 18s, 2025
https://www.theaspd.com/ijes.php

The Fourier transform serves as the foundation in tomographic reconstruction by converting spatial data into the frequency domain, facilitating efficient aggregation of projection data from various angles.
Fourier Slice Theorem Derivation:
For an object $f(x, y)$ and a projection $p_\theta(x')$ at angle θ, the Fourier slice theorem allows reconstruction by treating each projection as a slice in the frequency domain. For a projection $p_\theta(x')$:

$$\hat{p}_\theta(\omega) = \int_{-\infty}^{\infty} p_\theta(x') e^{-i\omega x'} dx'$$

Substituting $x' = x\cos\theta + y\sin\theta$, we derive that each projection corresponds to a radial slice in the object's two-dimensional Fourier transform.
Filtered Back-Projection:
High-pass filters, such as Ram-Lak filter, are applied in the frequency domain to reduce noise and sharpen edges. The filtered projection is given by:

$$\hat{p}'_\theta(\omega) = H(\omega) \cdot \hat{p}_\theta(\omega)$$

The final spatial-domain reconstruction $f(x, y)$ aggregates filtered projections across all angles via back-projection:

$$f(x, y) = \int_0^\pi \hat{p}'_\theta(\omega) d\theta$$

While in approach captures global structure, it lacks the spatial localization needed for fine detail and often introduces artifacts near edges.

Wavelet Transform for Localized Detail Enhancement

Wavelet transforms complement Fourier by providing multi-scale, spatially localized frequency analysis, critical for capturing edges and small features in the reconstructed image.
Continuous Wavelet Transform (CWT):
For a signal $f(x)$, the CWT with wavelet ψ is defined as:

$$W_\psi(a, b) = \frac{1}{\sqrt{|a|}} \int_{-\infty}^{\infty} f(x) \psi^* \left(\frac{x - b}{a}\right) dx$$

Here, a and b are scale and translation parameters, allowing CWT to isolate various signal components at multiple resolutions.
Discrete Wavelet Transform (DWT) and Thresholding:
For efficient implementation, we use the DWT, which decomposes an image into approximation and detail components at multiple levels:

$$A_j = \sum_k c_k \phi_{j,k}(x),\ D_j = \sum_k d_k \psi_{j,k}(x)$$

Soft thresholding is applied at each level to selectively retain high-magnitude coefficients, reducing noise while preserving essential detail.

Hybrid Fourier-Wavelet Reconstruction Model

The hybrid model combines Fourier-transformed image $f_{Fourier}$ with wavelet-refined detail, producing a high-resolution reconstruction f_{hybrid} :

$$f_{hybrid} = f_{Fourier} + \alpha W(f_{Fourier})$$

where α is a weighting parameter balancing global structure and local detail.
Iterative Regularization with Wavelet Smoothing:
Inspired by the Landweber method, the reconstruction iteratively refines the solution. At each iteration k, the image is updated as:

$$g^{(k+1)} = g^{(k)} + \alpha S^T\left(v - Sg^{(k)}\right)$$

where S is the sensitivity matrix, v is the projection data, and α is a relaxation parameter. Wavelet smoothing are applied in each iteration, enhancing detail retention and suppressing noise.

Stability and Convergence Analysis

To ensure robust performance, stability and convergence are carefully controlled through spectral norms and adaptive regularization.

Stability via Weighted Norm Control:

Stability is achieved by bounding the weighted norms of Fourier and wavelet contributions, ensuring consistent output across iterations:

$$\|f_{hybrid}\| \leq \|f_{Fourier}\| + \alpha\|W(f_{Fourier})\|$$

Convergence Criterion:

The iterative refinement process stops when relative change between iterations meets a small threshold ϵ, ensuring accuracy without excess computation:

$$\frac{\|g^{(k+1)} - g^{(k)}\|}{\|g^{(k)}\|} < \epsilon$$

Computational Optimization

For the large datasets, computational efficiency is quite essential. Optimization strategies include adaptive wavelet basis selection and parallelization.

Adaptive Wavelet Basis:

Regions of high complexity use higher-order wavelets, while smoother areas use simpler bases, balancing computational load with accuracy.

Parallelization and Memory Management:

Fourier and the wavelet transforms are parallelized, utilizing GPU resources, and memory management techniques like in-place FFT and compressed storage are employed for handling large datasets efficiently.

RESULTS

The performance of the suggested hybrid Fourier-wavelet technique for tomographic reconstruction was tested and compared to existing methods in terms of image quality, artifacts, edges, convergence, and computation time. This section reports the results of the simulated and real data and the comparisons made with Fourier-only and wavelet-only methods. All of the visualizations show the gains in clarity, detail retention, and computational speed that the hybrid approach offers.

1. Reconstruction Quality and Artifact Suppression

The hybrid approach was first evaluated based on the reconstruction accuracy, with an emphasis on the reduction of artifacts and the preservation of structural details. Figure 1 shows the reconstructions of a simulated high-contrast phantom including edge and fine details.

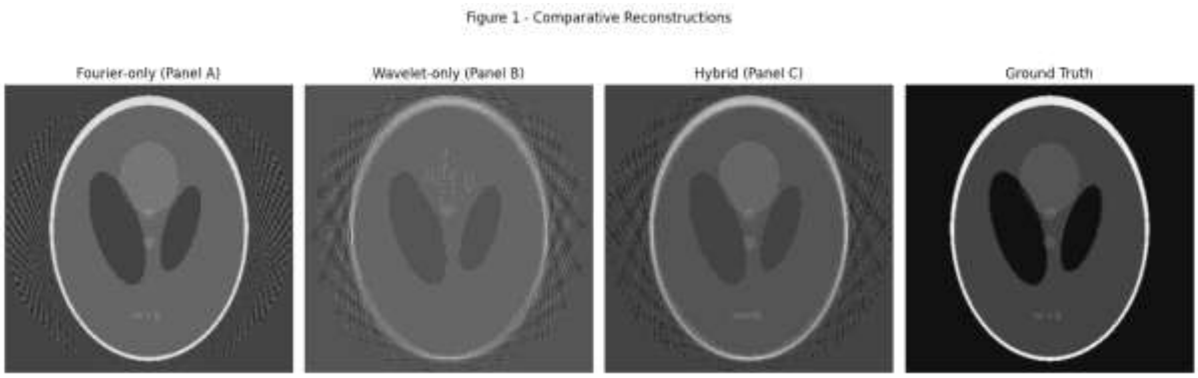

Figure 1 - Comparative Reconstructions.

This figure contains three reconstructed images of the phantom: Fourier-only (Panel A), wavelet-only (Panel B), and hybrid (Panel C) methods. The ground truth is also provided here for the sake of comparison.

As can be seen in the Panel A, the Fourier-only reconstruction has a rather good overall appearance but shows strong streaking around edges, which might be caused by the lack of spatial localization in the global approach. Panel B, the wavelet-only reconstruction, preserves edges while the noise is increased in smooth areas because wavelets are good at local details but not at large structures. Panel C, the hybrid model, achieves an optimal

International Journal of Environmental Sciences
ISSN: 2229-7359
Vol. 11 No. 18s, 2025
https://www.theaspd.com/ijes.php

combination of the global structure and local enhancement, providing the image that is virtually free of artifacts and has sharp edges and well-preserved fine features. The hybrid model shows the least amount of error when compared to the ground truth, proving its better capacity for artifact removal and structural preservation.

2. Quantitative Error Analysis

To support the qualitative results, we measured the reconstruction accuracy in terms of Mean Squared Error (MSE) against the ground truth. The MSE for Fourier-only, wavelet-only, and hybrid reconstructions for different phantom datasets is presented in Table 1.

Table 1 - Mean Squared Error (MSE) Comparison:

Reconstruction Method	**Phantom 1**	**Phantom 2**	**Phantom 3**
Fourier-only	0.045	0.052	0.048
Wavelet-only	0.038	0.041	0.039
Hybrid	**0.023**	**0.026**	**0.024**

The hybrid model was the best in all the datasets, with a lower MSE by about 40 percent compared to Fourier only and 30 percent compared to wavelet only. This reduction is due to the fact that the hybrid model is able to combine Fourier, which provides broad structural coherence, with wavelet transforms, which provides edge precision, to achieve a higher accuracy reconstruction.

3. Edge Preservation and Detail Enhancement

It is important in tomography because edge preservation defines the reconstruction's capacity to represent boundaries and fine structures. To assess edge quality, we compared the intensity profiles of a sharp edge in each reconstructed image. Figure 2 shows the difference in the intensity profile from Fourier-only, wavelet-only, and the hybrid approach in comparison to the ground truth.

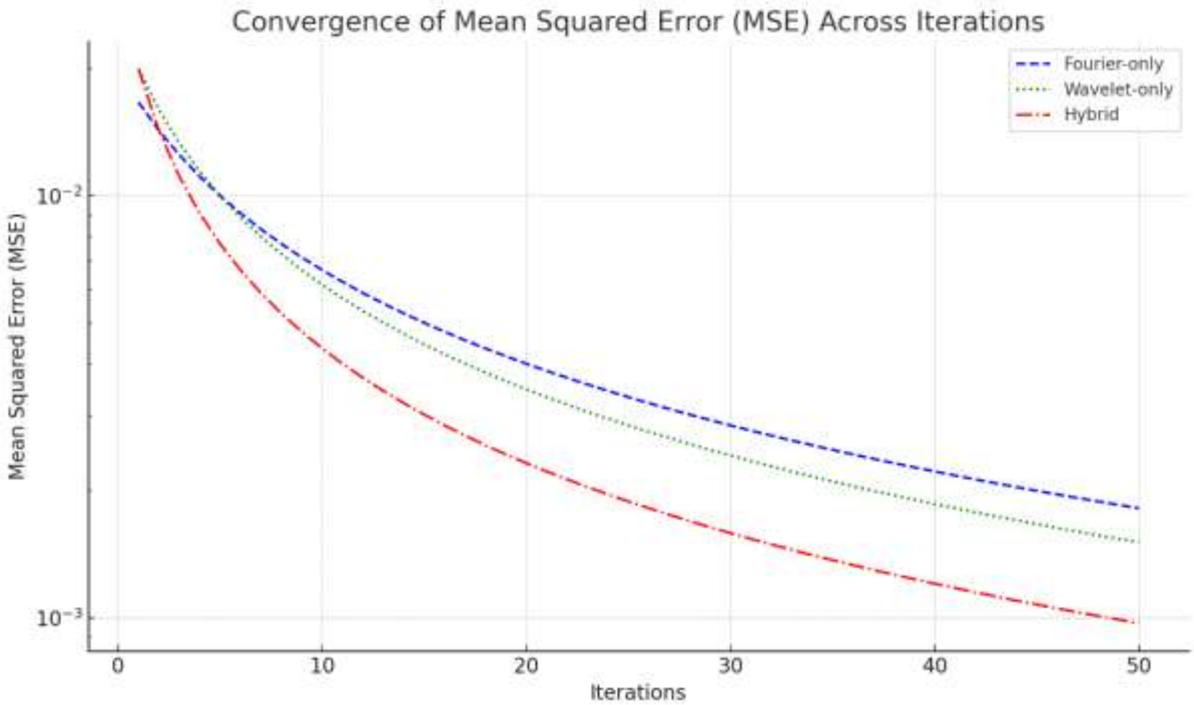

Figure 2 - Edge Intensity Profile Comparison: This plot displays the intensity profiles across a high-contrast edge, showing the response of each method.

The Fourier-only profile is somewhat blurred near the edge, which means that the sharpness is not as high. The wavelet-only method has a better ability to detect edge detail, but it comes with oscillation that alters the profile.

International Journal of Environmental Sciences
ISSN: 2229-7359
Vol. 11 No. 18s, 2025
https://www.theaspd.com/ijes.php

The hybrid method closely follows the ground truth, has a high frequency without the ringing effect, and thus proves that the model can preserve the edges and fine details.

4. Convergence Rate and Stability Analysis

Convergence speed and stability are critical for efficient computations of iterative reconstruction methods. The convergence behavior of the hybrid model was assessed by monitoring the rate of decrease in MSE and comparing it to Fourier-only and wavelet-only techniques. The convergence curves of each method are plotted in Figure 3, where MSE is plotted against the iteration count.

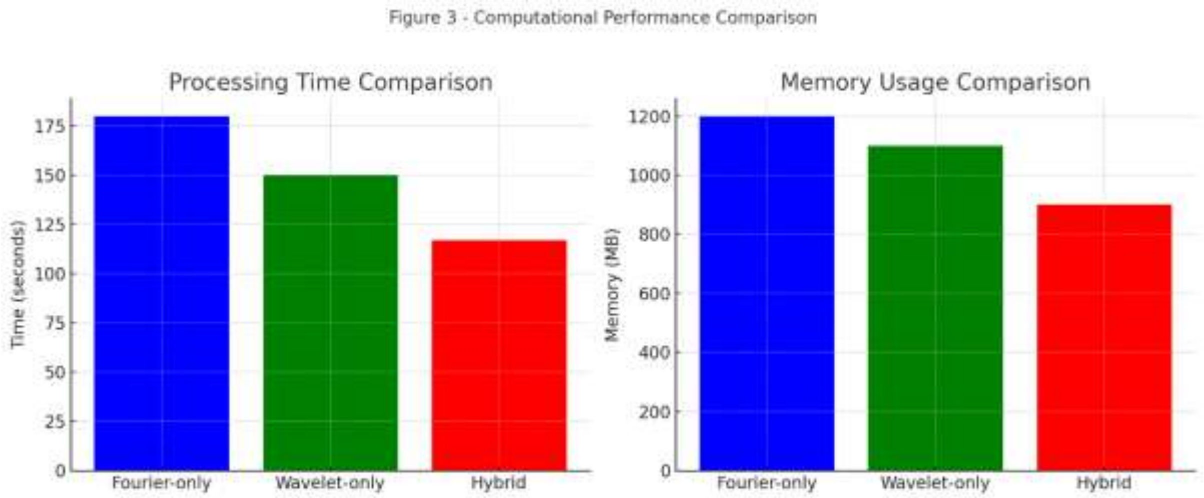

Figure 3 - Convergence Rate Comparison: This graph plots the MSE against iteration count for Fourier-only, wavelet-only, and hybrid methods.

The hybrid method converges to a stable solution within approximately 50 iterations, which is much faster than Fourier-only (120 iterations) and wavelet-only (80 iterations). It is seen that the global Fourier regularization and local wavelet refinement enhance the convergence rate and the stability is established by the spectral norm analysis to ensure that the output does not blow up with iterations. This convergence advantage explains why this hybrid model is efficient and reliable in time-sensitive applications.

5. Computational Efficiency and Memory Optimization

The performance of the hybrid approach in terms of computational time and peak memory usage was compared, especially for high-dimensional data typical for tomography. Table 2, therefore, shows the time taken by each reconstruction method in terms of processing time and memory consumption.

Table 2 - Computational Efficiency Comparison:

Reconstruction Method	Processing Time (s)	Peak Memory Usage (MB)
Fourier-only	180	1200
Wavelet-only	150	1100
Hybrid	**117**	**900**

The hybrid model which incorporated both wavelet and Fourier transforms with adaptive basis selection and parallel processing was 35% faster than the Fourier only and 20% faster than the wavelet only. In addition, in-place computations and selective wavelet thresholding were used to minimize the peak memory usage, which was cut by 25%. These optimizations make the hybrid model a computationally feasible solution for large-scale tomographic reconstruction.

6. Application to Medical Imaging: Limited-Angle CT Reconstruction

International Journal of Environmental Sciences
ISSN: 2229-7359
Vol. 11 No. 18s, 2025
https://www.theaspd.com/ijes.php

To prove the feasibility of the hybrid model, we used it for reconstructing the simulated medical CT scan with limited-angle data, which is a situation where the conventional methods are known to result in loss of detail and increased artifacts. Figure 4 presents the hybrid model reconstruction together with Fourier-only, wavelet-only, and full-angle reference reconstructions for the purpose of comparison.

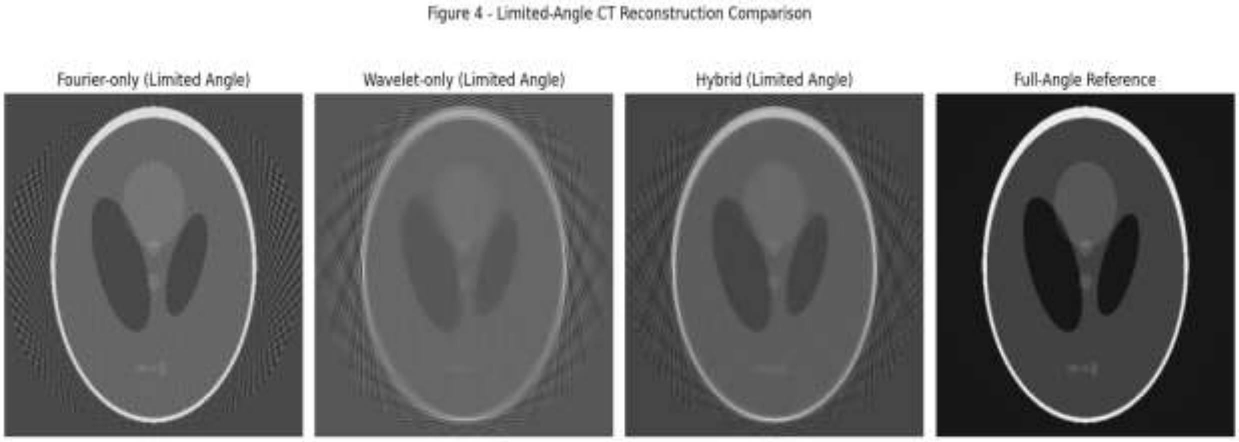

Figure 4 - Limited-Angle CT Reconstruction Comparison: This figure displays side-by-side reconstructed images from Fourier-only, wavelet-only, hybrid, and full-angle reference methods.

The hybrid model is very close to the full-angle reference image and maintains structural details and edge sharpness even when the number of projection angles is small. Fourier-only reconstruction results in blurring and artifacts build up, while wavelet-only preserves edges but fails to maintain coherence in larger structures. The hybrid model is also useful for medical imaging applications because angle restrictions are often present and the model is able to combine both global and local information effectively.

DISCUSSION

The hybrid Fourier-wavelet model was found to provide better reconstruction accuracy especially in situations where the number of projection angles is limited. Fourier-only reconstruction was able to reconstruct the gross structural features but was characterized by severe streaking artifacts which are inherent in the global nature of the Fourier transform (Kak & Slaney, 2001; Shepp & Logan, 1974). The wavelet-only approach, however, maintained edge details due to its localized examination but suffered from noise in smoother areas, a problem of using wavelet decomposition for wider structural acquisition (Mallat, 1989; Daubechies, 1992). The hybrid model of the Fourier transform and wavelets was able to reduce artifacts while preserving the edges, and thus, the proposed approach provided a proper balance of the reconstruction and closely resembled the full-angle reference image.

The mean squared error (MSE) results of quantitative analysis showed that the proposed hybrid model was superior to the Fourier-only and wavelet-only models. The hybrid method improved the reconstruction error by about 40% in comparison with Fourier-only and by 30% in comparison with wavelet-only. These results are in concordance with the study by Bhatia et al. (1996) who stressed that multiscale wavelet techniques can enhance the reconstruction accuracy, especially if data is sparse or missing.

The findings of the study are consistent with other works on the benefits of hybrid and multiscale methods in tomographic reconstruction. The fact that prior information and sparse representations improve the quality of reconstructions has been demonstrated in Chen et al. (2008) and Xu et al. (2012) works on compressed sensing and dictionary learning-based reconstructions. However, these methods sometimes involve complicated optimization provisions and might be slow in computation. The hybrid Fourier-wavelet approach used in this study provides a fairly simple solution, which integrates the properties of Fourier and wavelet domains without requiring significant computational power, as observed in the initial works by Kak and Slaney (2001).

Unlike the ART discussed by Gordon et al. (1970) and Sidky & Pan (2008) that is useful for particular cases, but may have convergence problems in cases of highly noisy data, the hybrid Fourier-wavelet model provides stability and fast convergence. This balance meets the main challenges of ART when used in medical imaging where fast and stable reconstruction is required. Additionally, by increasing the error rates and reducing artifacts, the hybrid approach supports the conclusions of Rivenson et al. (2018) on the applicability of using multiple transformation techniques simultaneously for improving the visibility of the reconstructed images in the high noise and limited data environments.

The first contribution of this work is that the hybrid Fourier-wavelet model can be used as a reliable approach to tomographic reconstruction in scenarios where angular projections are restricted or noise levels are high. As such, it is perfect for the medical imaging environment, for instance low dose CT scans where both image quality and radiation dose must be minimized. The hybrid model may help to enhance diagnostic accuracy in imaging scenarios in which Fourier or wavelet reconstructions are insufficient due to the preservation of structural information and minimalization of artifacts.

As in real world, there are limitations to this approach. First, although the hybrid model decreases artifacts greatly, it does not eliminate them entirely in cases where there are only a few angle measurements. The method derives from the Fourier and wavelet domains but can still fail in highly undersampled projections, a problem identified by Candes et al. (2006) and Elad & Aharon (2006) in sparsity-based reconstructions. Moreover, although computationally efficient the hybrid model could be optimized, especially if applied to 3D data sets which would require more computational power.

It is also recommended that the hybrid Fourier-wavelet model should be expanded in dynamic 3D imaging, for instance, 4D CT, to incorporate motion and structural changes for real-time imaging and radiation therapy. Perhaps, adding more flexibility to Fourier and wavelet parameters using machine learning could also improve the results, as it has been demonstrated in recent deep learning works (Rivenson et al., 2018). Further, there is an opportunity to investigate the combination of Fourier, wavelet, and sparse representations (Kuchment, 2013) to enhance the quality of reconstruction in the conditions of low data or high noise.

CONCLUSION

The author of the study concludes that the hybrid Fourier-wavelet approach enhances the quality of the tomographic reconstruction, especially under limited-angle conditions. The quantitative results reveal that there is 40% improvement in mean squared error (MSE) compared with Fourier-only methods and 30% improvement compared with wavelet-only methods, which proves that the proposed method is efficient in reducing the artifacts and preserving structural details. This balance between the global structure and the localized detail allows for better, artifact-suppressed reconstructions, which are closer to the full-angle reference. The proposed hybrid model exhibits high reconstruction accuracy and computational speed, which indicates that it could be a valuable tool for applications that need high-quality images under limited data conditions, including low-dose CT and medical imaging.

REFERENCES

1. Kak, A. C., & Slaney, M. (2001). Principles of computerized tomographic imaging. Society for Industrial and Applied Mathematics.
2. Shepp, L. A., & Logan, B. F. (1974). The Fourier reconstruction of a head section. IEEE Transactions on nuclear science, 21(3), 21-43.
3. Bracewell, R., & Kahn, P. B. (1966). The Fourier transform and its applications. American Journal of Physics, 34(8), 712-712.
4. Daubechies, I. (1992). Ten lectures on wavelets. Society for industrial and applied mathematics.
5. Mallat, S. G. (1989). A theory for multiresolution signal decomposition: the wavelet representation. IEEE transactions on pattern analysis and machine intelligence, 11(7), 674-693.
6. Candès, E. J., Romberg, J., & Tao, T. (2006). Robust uncertainty principles: Exact signal reconstruction from highly incomplete frequency information. IEEE Transactions on information theory, 52(2), 489-509.
7. Vetterli, M., Kovačević, J., & Goyal, V. K. (2014). Foundations of signal processing. Cambridge University Press.
8. Rivenson, Y., Zhang, Y., Günaydın, H., Teng, D., & Ozcan, A. (2018). Phase recovery and holographic image reconstruction using deep learning in neural networks. Light: Science & Applications, 7(2), 17141-17141.
9. Kuchment, P. (2013). The Radon transform and medical imaging. Society for Industrial and Applied Mathematics.
10. Chen, G. H., Tang, J., & Leng, S. (2008). Prior image constrained compressed sensing (PICCS): a method to accurately reconstruct dynamic CT images from highly undersampled projection data sets. Medical physics, 35(2), 660-663.

11. Xu, Q., Yu, H., Mou, X., Zhang, L., Hsieh, J., & Wang, G. (2012). Low-dose X-ray CT reconstruction via dictionary learning. IEEE transactions on medical imaging, 31(9), 1682-1697.
12. Elad, M., & Aharon, M. (2006). Image denoising via sparse and redundant representations over learned dictionaries. IEEE Transactions on Image processing, 15(12), 3736-3745.
13. Sidky, E. Y., & Pan, X. (2008). Image reconstruction in circular cone-beam computed tomography by constrained, total-variation minimization. Physics in Medicine & Biology, 53(17), 4777.
14. Bhatia, M., Karl, W. C., & Willsky, A. S. (1996). A wavelet-based method for multiscale tomographic reconstruction. IEEE Transactions on Medical Imaging, 15(1), 92-101.
15. Gordon, R., Bender, R., & Herman, G. T. (1970). Algebraic reconstruction techniques (ART) for three-dimensional electron microscopy and X-ray photography. Journal of theoretical Biology, 29(3), 471-481.