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Quantitative Assessment of Motion Consistency in Projection Data of Chest Tomosynthesis

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Abstract: Chest digital tomosynthesis (DTS) provides a compromise between conventional radiography and computed tomography in terms of radiation dose and diagnostic capability. Most reconstruction algorithms used in DTS assume a stationary object during acquisition. However, projection data are acquired over a finite time interval, during which internal anatomical structures may exhibit temporal variability. In this study, projection-domain intensity variations were analyzed to assess temporal consistency of DTS data. Mean intensity values were measured across multiple regions of interest (ROIs), forming temporal intensity profiles for anatomically distinct regions. Additionally, intensity profiles across anatomical transitions were evaluated in both projection data and reconstructed slices. The results show that while global intensity variations are primarily driven by acquisition geometry, certain regions exhibit local fluctuations, indicating reduced temporal consistency. Comparative analysis revealed that regions with increased variability correspond to degraded contrast and broadened transition boundaries in reconstructed slices. In particular, the heart–lung interface showed a significant contrast reduction compared to the stomach–lung interface, despite similar contrast levels in projection images. These findings indicate that even small temporal inconsistencies in projection data can lead to cumulative reconstruction errors. The proposed ROI-based analysis provides a simple approach for identifying such regions directly from projection data and suggests directions for improving reconstruction quality, including more consistent 3-D reconstruction of cardiac slices across different phases of the cardiac cycle.

Index Terms: Chest tomosynthesis, projection data, temporal consistency, image reconstruction, region of interest, intensity analysis, motion effects

1. Introduction

Digital chest tomosynthesis (DTS) has emerged over the last two decades as a promising imaging modality that bridges the gap between conventional projection radiography and computed tomography (CT) [1-5].

By acquiring a limited number of projection images over a restricted angular range and reconstructing a set of depth-resolved slices, DTS allows partial separation of overlapping anatomical structures while maintaining radiation doses substantially lower than those associated with CT examinations. The development of tomosynthesis as an

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imaging modality has been extensively studied by research groups in North America and Europe, where foundational work on system design and clinical applicability was established [1, 7, 8]. As a result, chest tomosynthesis has attracted increasing international interest for applications such as lung nodule detection, monitoring of pulmonary diseases, and evaluation of mediastinal structures [6-8].

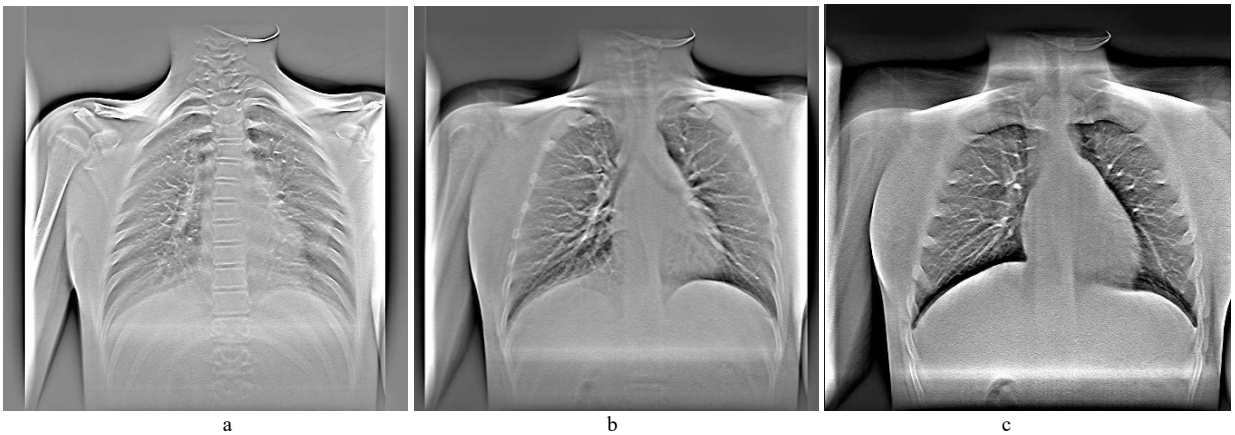
Compared with conventional chest radiography, tomosynthesis improves lesion conspicuity by reducing the effect of anatomical overlap. At the same time, the radiation dose required for a tomosynthesis acquisition remains significantly lower than that of CT, typically on the order of several times the dose of a single chest radiograph but still an order of magnitude lower than a typical chest CT examination. These characteristics have been confirmed in multiple studies conducted across different countries and clinical settings, highlighting the growing role of DTS in diagnostic imaging workflows [1, 6]. Because of this intermediate position between two established imaging techniques, DTS is increasingly considered a valuable imaging modality in clinical workflows that require repeated imaging or population screening [6].

Table 1 presents a comparative analysis of digital radiography (DR), digital tomosynthesis (DT), and computed tomography (CT) systems used in medical practice. Radiography provides the highest spatial resolution (up to 5 lp/mm), whereas CT demonstrates the lowest (approximately 1 lp/mm), which is sufficient for lung imaging but may be inadequate for detecting fine bone structures. Digital tomosynthesis occupies an intermediate position with a resolution of up to 2 lp/mm, enabling visualization of most clinically relevant pathologies. Unlike radiography, both DT and CT support three-dimensional visualization; moreover, DT demonstrates higher depth resolution (up to 1.6 lp/mm) compared to CT (up to 1 lp/mm). In terms of radiation dose, DR has the lowest exposure (up to 0.1 mSv), CT the highest (up to 4–8 mSv), while DT maintains a moderate dose (up to 0.4 mSv) consistent with the ALARA principle. Diagnostic sensitivity follows a similar trend: DR shows the lowest sensitivity (0.64), DT improves it significantly (0.92), approaching CT performance (0.98). These characteristics have been investigated in both engineering and clinical studies, including recent developments in mobile tomosynthesis systems [2, 5]. DT systems can also be implemented on existing radiographic equipment, making them more cost-effective compared to CT, whose cost may be 7–10 times higher depending on system configuration [2].

Table 1. Comparative Characteristics of DR, DT and CT systems

Parameter	DR	DT	CT
Resolution, lp/mm	Up to 5.0	Up to 2.0	Up to 1.0
Depth resolution, lp/mm	-	Up to 0,8	Up to 1.0
Dose, mSv	Up to 0.1	Up to 0.4	Up to 4
3D image	-	+	+
Sensitivity	0.64	0.92	0.98

Technically, tomosynthesis relies on the acquisition of a sequence of projection images while the X-ray tube moves relative to the detector along a predefined trajectory. The angular range of this motion is typically limited, often spanning approximately 20°–60°. During acquisition, the detector records a set of projection images corresponding to different viewing angles, which are later processed using dedicated reconstruction algorithms to generate a stack of quasi-tomographic slices [7-9]. Fig. 1. shows tomosynthesis slices at different depths.



a b c

Fig. 1. Example of tomosynthesis slices: (a) the 60th slice corresponding to the depth of the spine; (b) the 100th slice corresponding to the level of tracheal bifurcation into the bronchi; (c) the 140th slice, where the heart and lungs are clearly visualized.

Several reconstruction approaches have been proposed for tomosynthesis, including shift-and-add techniques, modified filtered backprojection algorithms adapted to limited-angle geometry, and iterative reconstruction methods that incorporate system models and prior constraints. Regardless of the specific algorithm used, reconstruction methods generally rely on the assumption that the imaged object remains geometrically stable during the acquisition process. Under

this assumption, projection images acquired from different angles correspond to the same spatial distribution of attenuation coefficients, allowing the reconstruction algorithm to focus structures located at a specific depth while suppressing structures located outside the reconstruction plane.

In chest tomosynthesis imaging, the acquisition of projection data typically lasts several seconds. During this time interval, most thoracic anatomical structures may be considered approximately stationary, especially when patients are instructed to hold their breath during the scan. To further minimize motion, imaging systems commonly employ patient positioning supports, such as chin rests or stabilization frames, which help maintain a consistent posture throughout the acquisition.

Despite these precautions, projection consistency may still be affected by several sources of motion. These include residual respiratory motion, involuntary body movements, and physiological processes associated with internal organ dynamics. Such motion may introduce inconsistencies between successive projection images, which can propagate into reconstruction artifacts or reduced slice sharpness.

Motion-related artifacts in tomographic imaging systems have been widely studied, particularly in computed tomography. In tomosynthesis, however, the limited angular range and sequential acquisition of projections create additional sensitivity to temporal inconsistencies in the projection dataset. Even relatively small temporal variations in attenuation patterns may affect reconstruction quality, especially in regions where dynamic anatomical structures are located near diagnostically relevant tissues.

Previous studies have demonstrated that tomosynthesis reconstruction is sensitive to inconsistencies between projections and that motion during acquisition may result in characteristic artifacts such as blurring, ghosting, or reduced contrast in reconstructed slices. Understanding the temporal stability of projection data is therefore important for improving reconstruction algorithms and for assessing the robustness of tomosynthesis systems in clinical practice.

One possible approach to evaluating projection stability is to analyze temporal variations of image intensity within selected regions of interest across the projection sequence. Statistical descriptors such as mean intensity, variance, or spectral characteristics may reveal the presence of dynamic components in the projection data. Regions containing static anatomical structures are expected to exhibit relatively smooth variations related primarily to geometric factors, while regions influenced by dynamic processes may show additional temporal fluctuations.

In particular, periodic or quasi-periodic components may appear in projection data when dynamic structures within the thoracic cavity change their configuration during the acquisition sequence. Detecting and quantifying such components can provide insight into the temporal behavior of projection data and into the influence of dynamic structures on tomosynthesis reconstruction.

The analysis of temporal consistency in projection data is therefore relevant not only for understanding motion-related artifacts but also for improving acquisition protocols and reconstruction methods in tomosynthesis imaging.

An additional aspect that may influence temporal consistency of projection data is the fact that mechanical activity of thoracic organs is not necessarily spatially uniform. The motion of cardiac walls, for example, may vary in amplitude and timing across different regions of the myocardium. Under normal physiological conditions, myocardial motion patterns are relatively coordinated, but various pathological conditions—such as ischemic heart disease, regional wall motion abnormalities, or cardiomyopathies—may alter the local mobility of cardiac tissue. These variations may result in differences in the magnitude or spatial distribution of motion-related intensity changes observed in projection images. Although the present work does not aim to characterize specific physiological mechanisms, the potential presence of spatially heterogeneous motion patterns should be considered when analyzing temporal intensity variations in projection-domain data.

2. Problem Statement

Although chest tomosynthesis reconstruction algorithms generally assume geometric consistency between projections, in practice the projection dataset may contain temporal variations caused by dynamic anatomical processes and small patient movements during acquisition. These variations may introduce inconsistencies in the projection data that can affect reconstruction accuracy and image quality [10-16].

At present, the influence of such temporal variations on projection stability is not fully characterized in chest tomosynthesis systems. In particular, the presence of dynamic structures within the thoracic cavity may introduce localized temporal intensity variations in the projection images that differ from those observed in regions containing predominantly static anatomical structures.

A systematic quantitative framework for evaluating temporal consistency in tomosynthesis projection data is therefore required. Such a framework should allow the comparison of different anatomical regions in terms of their temporal stability and should provide objective indicators for detecting dynamic components in projection sequences.

In this work, projection images obtained during chest tomosynthesis acquisition are analyzed using region-of-interest–based statistical descriptors in order to evaluate the temporal stability of attenuation patterns across the projection sequence. By comparing the temporal behavior of regions associated with static anatomical structures to regions influenced by dynamic processes, it becomes possible to identify and quantify periodic components present in the projection data.

The objective of this study is therefore to develop a quantitative approach for assessing motion consistency in projection-domain data of chest tomosynthesis and to evaluate how dynamic structures influence temporal intensity variations within the projection sequence.

3. Materials and Methods

3.1. Data acquisition and preprocessing

The study was performed using projection data obtained from a chest digital tomosynthesis system. The acquisition protocol consisted of a sequence of low-dose X-ray projections acquired over a limited angular range within approximately 6 seconds. During the acquisition, the patient was instructed to remain stationary and maintain a fixed position using a chin support to minimize motion artifacts unrelated to physiological processes.

The projection data were processed as image stacks in Fiji (ImageJ). Due to variation in global image intensity across projections caused by changes in the effective X-ray path length at different projection angles, an intensity normalization procedure was applied. For each projection, the mean intensity was measured within a reference region located in an air-equivalent area (empty corner of the image).

In addition to intensity normalization, a geometric alignment procedure was performed to compensate for residual vertical shifts between projections. These shifts may arise from slight patient motion or mechanical inaccuracies during acquisition and can introduce artificial variability in subsequent analysis.

Let $I_k(x, y)$ denote the intensity of the k-th projection image. For each projection, a vertical shift Δy_k was estimated relative to a reference projection $I_{ref}(x, y)$. The shift was determined by maximizing the normalized cross-correlation along the vertical axis:

$$\Delta y_k = \arg\max_{\Delta y} \sum_{x,y} I_k(x, y + \Delta y) I_{ref}(x, y) \tag{1}$$

To reduce sensitivity to noise and local anatomical changes, the estimation was performed either:

- within a selected region of interest (ROI), or
- using vertically averaged intensity profiles:

$$P_k(y) = \frac{1}{N_x} \sum_{x} I_k(x, y) \tag{2}$$

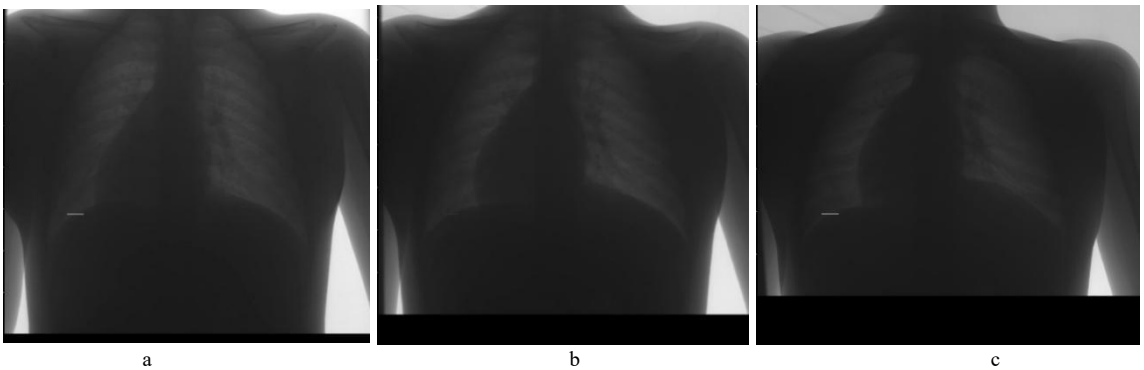
In this case, the vertical shift was obtained by:

$$\Delta y_k = \arg\max_{\Delta y} \sum_{y} P_k(y + \Delta y) P_{ref}(y) \tag{3}$$

After estimating Δy_k, each projection was aligned by applying a vertical translation:

$$\widetilde{I_k}(x, y) = I_k(x, y \Delta y_k) \tag{4}$$

Interpolation (e.g., linear interpolation) was used when non-integer pixel shifts were required.



a b c

Fig. 2. Projections from a single tomosynthesis case: (a) 60, (b) 100, (c) 140. The projections have been aligned along the vertical axis

This alignment procedure ensured that corresponding anatomical structures remained vertically consistent across projections, thereby improving the reliability of temporal intensity analysis and reducing artificial variability introduced by geometric misalignment. The result of this procedure is presented in Fig. 2.

A normalization factor was then computed relative to the first projection, and each projection was scaled accordingly to compensate for global intensity drift.

3.2. Exploratory analysis of projection variability

As an initial stage of the study, an exploratory analysis of intensity variations across projection images was performed. The objective of this step was to assess whether anatomical structures exhibit measurable changes in their projection-domain representation over the acquisition sequence.

Several regions of interest (ROIs) were defined within anatomically relevant areas and tracked across all projections. For each ROI, the mean intensity value was calculated for every projection, forming temporal intensity profiles.

This preliminary analysis revealed that certain regions demonstrate non-uniform behavior across projections, including gradual trends and local fluctuations. These variations may originate from a combination of factors, including changes in projection geometry, variation in effective attenuation paths, and potential motion of internal structures.

Although this stage does not directly provide quantitative diagnostic metrics, it serves as an important basis for further analysis by identifying regions where projection data exhibit reduced temporal consistency.

This observation motivated further investigation of how such variability affects reconstructed image quality.

3.3. Region of interest (ROI) selection and intensity analysis

To evaluate local temporal variations in projection data, multiple regions of interest (ROIs) were manually defined on the projection images. The selected ROIs corresponded to anatomically distinct regions with different expected motion characteristics:

- ROI1: apex of the heart
- ROI2: lateral contour of the left ventricle
- ROI3: central cardiac region
- ROI4: subdiaphragmatic region (stomach area)

Each ROI was applied consistently across all projections in the stack. For every projection, the mean intensity within each ROI was measured. This resulted in a temporal intensity profile I(t)for each region over the projection sequence.

These profiles were analyzed to identify:

- global intensity trends associated with projection geometry,
- local deviations from the trend,
- presence of oscillatory or quasi-periodic components.

3.4. Intensity profile analysis of anatomical transitions

To assess the influence of projection consistency on reconstructed image quality, intensity profiles were extracted across anatomical boundaries in both projection images and reconstructed slices.

Two types of transitions were analyzed:

- heart–lung interface (HL)
- stomach–lung interface (SL)

Linear intensity profiles were manually defined across these boundaries. For each profile, the transition characteristics were evaluated, including:

- intensity difference between regions,
- gradient steepness,
- transition width.

Profiles obtained from projection data were compared with corresponding profiles extracted from reconstructed tomosynthesis slices.

3.5. Contrast evaluation

Due to the presence of negative intensity values in reconstructed slices, all intensity measurements were offset prior to contrast calculation:

$$I' = I + 1000 \tag{5}$$

This transformation ensures a strictly positive intensity range while preserving relative differences between regions. Contrast between two regions was calculated using the following expression:

$$C = \frac{I_1' - I_2'}{I_2'} \tag{6}$$

where:

I_1'— intensity of the target region (e.g., heart or stomach),
I_2''— intensity of the reference region (lungs).

This definition provides a normalized measure of contrast consistent with the evaluation performed on projection data.

In addition to normalized contrast, the absolute intensity difference was also considered:

$$\Delta I = |I_1 - I_2| \tag{7}$$

This metric was used to support interpretation of contrast behavior independently of normalization effects.

3.6. Assessment of temporal consistency

Temporal consistency of projection data was evaluated by analyzing deviations of ROI intensity profiles from the global trend. Regions exhibiting increased variability or oscillatory behavior were interpreted as potentially influenced by dynamic anatomical processes.

The relationship between projection-domain variability and reconstruction-domain contrast degradation was assessed qualitatively by comparing ROI behavior with corresponding anatomical regions in reconstructed slices.

4. Results

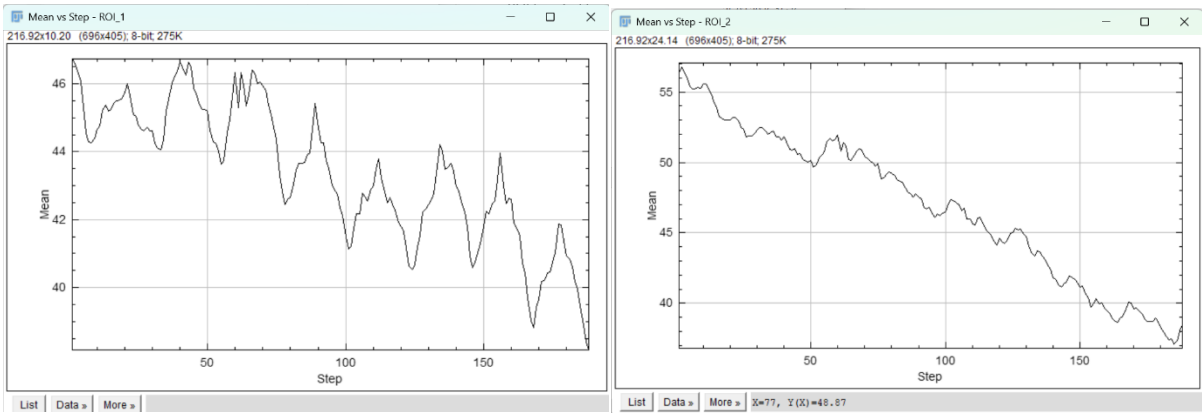
4.1. Projection-domain intensity variability

The analysis of mean intensity values within selected regions of interest (ROIs) across projection images revealed the presence of both global and local variations in the projection data.

A consistent global trend of decreasing intensity was observed across all ROIs as a function of projection index (Fig. 3.a–1.d). This behavior is attributed to changes in the effective X-ray path length caused by increasing projection angle during acquisition, resulting in increased attenuation and corresponding reduction in detected intensity.

However, superimposed on this global trend, certain regions demonstrated additional local fluctuations.

In particular, the ROI located in the apex region (ROI1) exhibited pronounced oscillatory behavior (Fig. 3.a), deviating from the monotonic trend observed in more stable regions. In contrast, the ROI corresponding to the lateral contour of the structure (ROI2) showed predominantly smooth intensity variation with minimal local fluctuations (Fig. 3.b).



a b

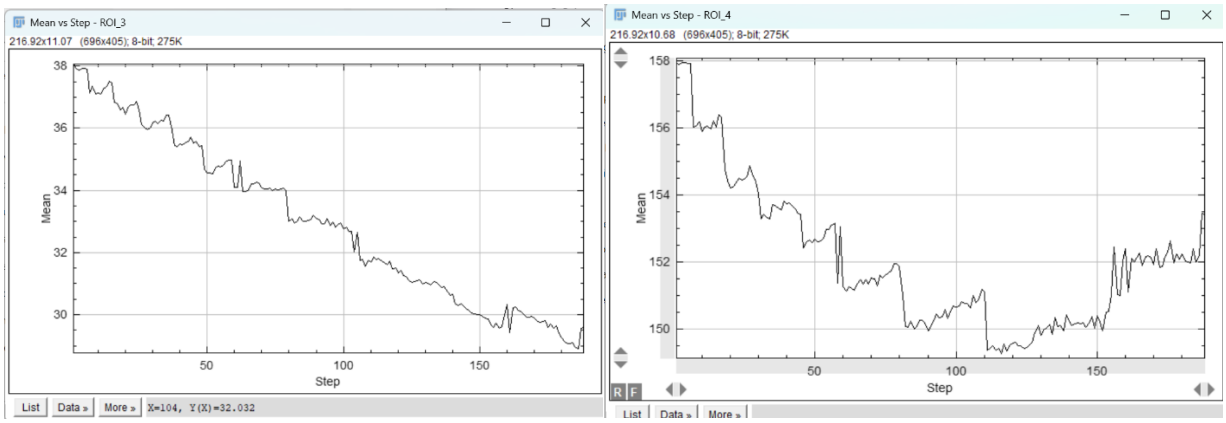


Fig. 3. Mean intensity variation in a - ROI1 (apex region); b - in ROI2 (lateral contour region); c - ROI3 (central region); d - ROI4 (subdiaphragmatic/stomach region) across projection index.

Intermediate behavior was observed in the central region (ROI3), where small-amplitude fluctuations were present but less pronounced than in ROI1 (Fig. 3.c). Regions located outside the central thoracic structures, such as the subdiaphragmatic area (ROI4), demonstrated predominantly monotonic intensity variation consistent with projection geometry effects (Fig. 3.d).

These findings indicate that temporal consistency of projection data is spatially non-uniform and depends on the anatomical region.

4.2. Intensity profile comparison: projections vs reconstructed slices

To evaluate the impact of projection-domain variability on reconstructed image quality, intensity profiles across anatomical transitions were analyzed both in projection images and in reconstructed slices.

In projection images, the intensity transitions across both heart–lung and stomach–lung interfaces demonstrated similar characteristics, with comparable transition slopes and contrast levels (Fig. 4.a–b). Quantitative evaluation confirmed that the contrast values for both transitions were approximately equal (~0.28), indicating consistent representation of these boundaries in the projection domain.

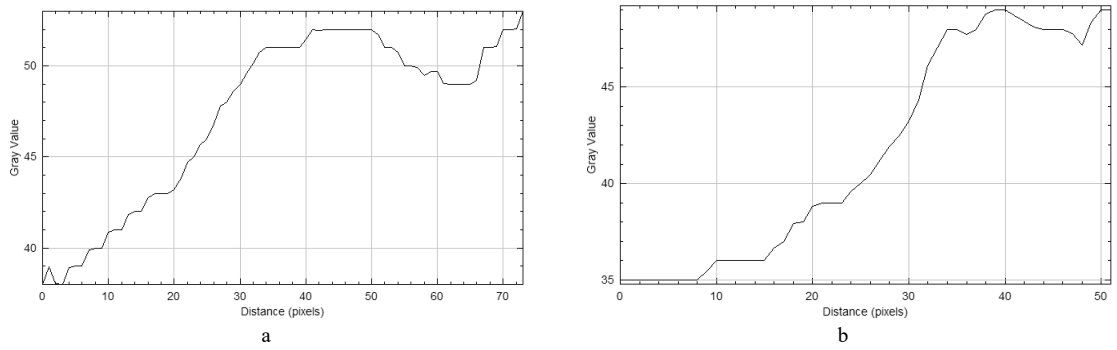


Fig. 4. Intensity profile across a - the heart–lung interface; b - stomach–lung in projection data.

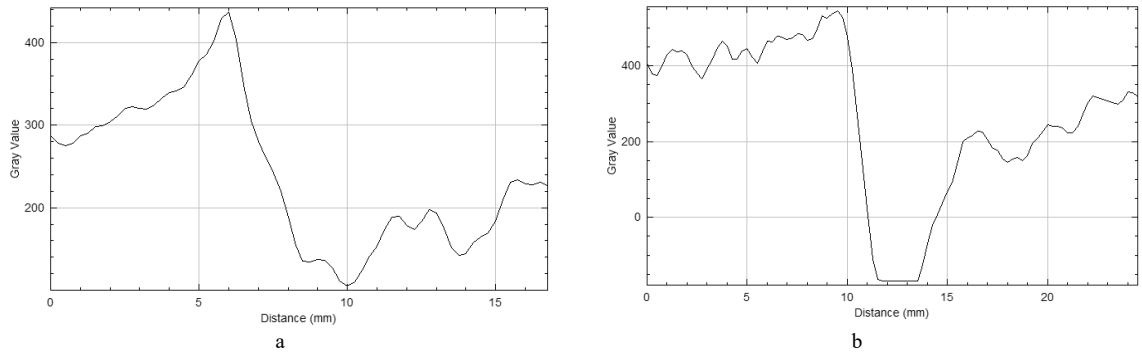


Fig. 5. Intensity profile across a - the heart–lung and b - stomach–lung interface in reconstructed slices. Contrast analysis in reconstructed slices

In contrast, analysis of reconstructed slices revealed significant differences between these transitions. The stomach–lung interface preserved a relatively sharp intensity transition, while the heart–lung interface exhibited a noticeably reduced contrast and a more gradual transition profile (Fig. 5.a–b).

Quantitative contrast analysis of reconstructed slices confirmed the observed differences between anatomical regions.

After offset correction of intensity values, the contrast between regions was calculated. The heart–lung transition exhibited a significantly lower contrast value ($C \approx 0.155$) compared to the stomach–lung transition ($C \approx 0.385$).

Additionally, the absolute intensity difference between regions further emphasized this disparity:

- heart–lung: $\Delta I \approx 220$
- stomach–lung: $\Delta I \approx 570$

The reproducibility of the observed effect was verified across 21 projection series and their corresponding reconstructed tomosynthesis slices. It was found that, despite similar contrast levels in projection images for both anatomical transitions (heart–lung and stomach–lung), typically ranging from $C \approx 0.35$ to 0.42, the reconstructed slices demonstrate a systematic divergence.

In particular, the contrast for the heart–lung interface in reconstructed slices was consistently reduced, falling within the range of $C \approx 0.13$–0.17. In contrast, the stomach–lung interface preserved its contrast characteristics, remaining within the range of $C \approx 0.36$–0.41.

These results confirm that the contrast degradation effect is stable and reproducible and is primarily associated with anatomically dynamic regions, rather than being a random or dataset-specific phenomenon.

4.3. Interpretation of spatial variability

The observed differences suggest that projection-domain temporal variability affects reconstructed image quality in a spatially dependent manner.

Regions demonstrating increased local fluctuations in projection data (e.g., ROI1) correspond to areas where reconstructed slices exhibit reduced contrast and broadened transition profiles. Conversely, regions with stable projection-domain behavior (e.g., ROI4) preserve sharper transitions in reconstructed images.

This relationship supports the hypothesis that temporal inconsistency in projection data contributes to degradation of reconstructed image quality, particularly in regions associated with dynamic anatomical structures.

5. Discussion

The obtained results demonstrate that projection data in chest tomosynthesis are not fully temporally consistent, even under conditions where patient motion is minimized. The observed variations in ROI-based intensity measurements indicate the presence of structured, non-random fluctuations, which can be interpreted as a consequence of internal physiological motion.

The analysis of brightness profiles across different anatomical transitions showed that projection images exhibit relatively stable contrast characteristics. However, after reconstruction, the same regions demonstrate noticeable variability, particularly in areas adjacent to the heart. This discrepancy suggests that the reconstruction process amplifies inconsistencies present in projection data, especially when motion is not explicitly modeled.

One of the key findings of this study is the presence of a quasi-periodic component in the intensity variations for selected ROIs associated with cardiac structures. Although the method does not explicitly identify the cardiac cycle, the detected periodicity is consistent with physiological motion patterns. At the same time, other ROIs located outside the heart region show predominantly monotonic trends related to geometric factors, such as varying X-ray path length across projection angles.

These observations highlight an important limitation of standard tomosynthesis reconstruction approaches, which typically assume static object conditions during acquisition. In reality, even small periodic motions can introduce inconsistencies that lead to local contrast degradation and blurring in reconstructed slices, particularly in mediastinal regions.

Importantly, the results suggest not only the need for motion compensation but also open an alternative perspective. Instead of treating motion solely as a source of artifacts, the temporal variability embedded in projection data may be exploited as an additional source of information. In particular, the detected periodic component can be used to segment projection data into subsets corresponding to different motion phases.

Such an approach may enable the reconstruction of multiple image volumes, each corresponding to a specific phase of the cardiac cycle. Although each individual reconstruction would be based on a reduced number of projections and therefore have lower spatial resolution, these phase-resolved reconstructions could provide valuable dynamic information. This represents a trade-off between spatial resolution and temporal consistency.

From this perspective, the proposed ROI-based analysis can serve as a simple and computationally efficient tool for identifying regions affected by motion and estimating the degree of temporal inconsistency. This information can be further used to guide advanced reconstruction strategies, including phase-based grouping of projections or adaptive

weighting schemes.

Additionally, this method may be useful for evaluating the stability of acquisition conditions and identifying datasets where motion effects are likely to significantly impact diagnostic quality. This is particularly relevant for mobile or resource-limited systems, where acquisition conditions are less controlled.

6. Conclusion

In this study, a quantitative ROI-based approach for assessing motion consistency in projection data of chest tomosynthesis was proposed and experimentally validated.

The results demonstrate that even under controlled acquisition conditions, projection data exhibit measurable temporal variability, which is particularly pronounced in regions associated with cardiac motion. The presence of a quasi-periodic component in intensity variations confirms that physiological motion contributes to inconsistencies in projection data and affects the quality of reconstructed slices.

It was shown that while projection images maintain relatively stable contrast characteristics, reconstruction amplifies the effects of temporal inconsistency, leading to degradation of image quality in specific anatomical regions. This highlights the importance of accounting for motion in tomosynthesis reconstruction algorithms.

Beyond identifying motion-related artifacts, the proposed method provides a practical way to estimate the magnitude and structure of temporal variations directly from projection data. This creates opportunities for improving reconstruction quality through motion-aware processing.

Furthermore, the findings suggest a promising alternative approach: instead of reconstructing a single static volume, projection data can be partitioned into subsets corresponding to different phases of motion. This enables the reconstruction of multiple volumes representing different stages of the cardiac cycle.

Although each such reconstruction may have reduced spatial resolution due to the smaller number of projections, the resulting phase-resolved images can provide additional functional information that is not available in conventional tomosynthesis. Thus, a set of lower-resolution reconstructions may collectively offer higher diagnostic value by capturing temporal dynamics.

In this context, the proposed ROI-based analysis can be used as a preliminary step for detecting motion-sensitive regions and estimating temporal periodicity, which can then be incorporated into advanced reconstruction frameworks.

Overall, the study demonstrates that temporal variability in tomosynthesis is not only a limitation but also a potential source of additional information. Future work will focus on integrating phase-based reconstruction strategies and evaluating their impact on both structural and functional imaging tasks.

All the Declarations and Statements

Author Contribution Statement

Oleksandra Miroshnychenko – Conceptualization, Investigation, and Visualization: Developed the overall research idea, conducted the experimental studies, and prepared figures and visual materials.

Yurii Khobta – Software, Investigation, and Writing – Formatting: Responsible for code development, execution of experimental series, and formatting of the manuscript.

Sergii Miroshnychenko – Supervision, Methodology, and Writing – Review & Editing: Provided overall project management, refined the research concept, contributed to mathematical formulation, and critically revised the manuscript for technical accuracy and coherence.

Andrii Nevgasymyi – Software, Writing – Review & Editing, and Conceptual Support: Contributed to programming tasks, participated in manuscript preparation and editing, and supported the development of general research ideas.

All authors have read and agreed to the published version of the manuscript.

Conflict of Interest Statement

The Authors declared no conflicts of interest.

Funding Declaration

This research received no external funding.

Data Availability Statement

The data that support the findings of this study are from the corresponding author upon reasonable request.

Ethical Declarations

This study did not involve human participants or animals.

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Declaration of Generative AI in Scholarly Writing
During the preparation of the manuscript, the authors carefully reviewed the content and take full responsibility for the accuracy and integrity of the manuscript.

Abbreviations
The following abbreviations are used in this manuscript:

DTS – Digital Tomosynthesis
ROI – Region of Interest
CT – Computed Tomography
DR – Digital Radiography

Appendix A\B\C…, with appendix tile
None.

References

[1] J. T. Dobbins III, “Tomosynthesis Imaging: Recent Advances and Clinical Applications,” Med. Phys., vol. 45, no. 6, pp. e639–e654, 2018. doi: 10.1002/mp.12957.
[2] O. Miroshnychenko, S. Miroshnychenko, A. Nevgasymyi, R. Panteyev, D. Radko, “The Concept of a Mobile X-Ray System with Tomosynthesis,” Proc. IEEE Int. Conf. Electronics and Nanotechnology (ELNANO), 2024, pp. 452–455.
[3] A. Kumar, S. Singh, “Contrast Enhancement Techniques for Medical Images: A Review,” Int. J. Image, Graphics and Signal Processing (IJIGSP), MECS Press, vol. 10, no. 3, pp. 1–10, 2018. doi: 10.5815/ijigsp.2018.03.01.
[4] H. Zhao, G. Wang, “Motion Compensation in Tomosynthesis Reconstruction: A Review,” Med. Phys., vol. 45, no. 3, pp. e168–e182, 2018. doi: 10.1002/mp.12712.
[5] O. Miroshnychenko, S. Miroshnychenko, Y. Khobta, A. Nevgasymyi, “Assessment of Compliance of Digital X-ray Tomosynthesis Images with Image Quality Requirements,” Proc. IEEE ELNANO, 2022, pp. 401–404.
[6] O. Miroshnychenko, S. Miroshnychenko, Y. Khobta, A. Nevgasymyi, “Contrast Comparison of Chest Pathologies in Radiography and Tomosynthesis,” Proc. ISETC, 2020.
[7] M. A. Sattar, S. Lee, “A Review of Image Reconstruction Techniques in Medical Imaging,” Int. J. Information Technology and Computer Science (IJITCS), MECS Press, vol. 9, no. 1, pp. 1–10, 2017. doi: 10.5815/ijitcs.2017.01.01.
[8] I. Sechopoulos, S. Vedantham, “Digital Breast Tomosynthesis: Current State and Future Perspectives,” Med. Phys., vol. 46, no. 12, pp. e913–e928, 2019. doi: 10.1002/mp.13701.
[9] Y. Zhang, H. Yu, G. Wang, “A Review of Computational Algorithms for Tomographic Imaging,” IEEE Trans. Med. Imaging, vol. 37, no. 2, pp. 517–530, 2018. doi: 10.1109/TMI.2017.2766876.
[10] R. Sharma, P. Gupta, “Region of Interest-Based Medical Image Analysis: Recent Advances,” Int. J. Image, Graphics and Signal Processing (IJIGSP), MECS Press, vol. 9, no. 5, pp. 12–20, 2017. doi: 10.5815/ijigsp.2017.05.02.
[11] K. Verma, A. Jain, “Noise Analysis and Reduction Techniques in Medical Imaging,” Int. J. Intelligent Systems and Applications (IJISA), MECS Press, vol. 9, no. 9, pp. 45–52, 2017. doi: 10.5815/ijisa.2017.09.05.
[12] J. Granstedt et al., “Clinical Evaluation of Chest Tomosynthesis for Pulmonary Nodule Detection,” Eur. Radiol., vol. 27, no. 12, pp. 4979–4987, 2017. doi: 10.1007/s00330-017-4851-1.
[13] M. Båth et al., “Improved Detection of Pulmonary Nodules with Digital Chest Tomosynthesis,” Eur. Radiol., vol. 26, no. 5, pp. 1342–1349, 2016. doi: 10.1007/s00330-015-3922-7.
[14] J. T. Dobbins III, “Advanced Tomosynthesis Imaging Techniques and Clinical Applications,” Med. Phys., vol. 45, no. 6, pp. e639–e654, 2018.
[15] S. Patel, R. Mehta, “Medical Image Processing Techniques for Diagnosis: A Survey,” Int. J. Intelligent Systems and Applications (IJISA), MECS Press, vol. 10, no. 2, pp. 1–9, 2018. doi: 10.5815/ijisa.2018.02.01.
[16] I. Sechopoulos, “Advances in Digital Breast Tomosynthesis Imaging,” Med. Phys., vol. 47, no. 3, pp. e102–e115, 2020. doi: 10.1002/mp.13970.Shor, P. W. (1999). Polynomial-time algorithms for prime factorization and discrete logarithms on a quantum computer. SIAM Journal on Computing, 26(5), 1484-1509. DOI: 10.1137/S0097539791191494

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