A COMPREHENSIVE REVIEW ON MULTI-VIEW CHEST X-RAY 3D RECONSTRUCTION FOR ENHANCED THORACIC DISEASE DIAGNOSIS

[1]Mr. Birudev Yele, [2]Dr. Waseem Mir
Faculty of Science and Technology , School of Computational Sciences , JSPM UNIVERSITY, PUNE
Wagholi, Pune 412207, Maharashtra, India[1,2]
birudevyele2000@gmail.com[1], waseemmir78177@gmail.com[2]

ABSTRACT

In thoracic medicine, accurate diagnosis is crucial to patient care. If not identified early and correctly, thax-related conditions such as pneumonia, tuberculosis, lung cancer, and other cardiopulmonary diseases can have serious health consequences. Therefore, one of the most important steps in improving patient outcomes is increasing diagnostic accuracy. Because of their affordability, speed, and accessibility, chest X-rays (CXRs) are one of the most widely used imaging methods; however, they are essentially 2D predictions of 3D anatomical structures. The depth information is compressed by this flat representation, which frequently results in overlapping anatomical features. Because of this, it may be difficult to determine the precise location, size, or depth of lesions, which could result in a misdiagnosis or misunderstanding. Techniques for multi-view 3D reconstruction are being investigated in order to get around the drawbacks of 2D imaging. The goal of these techniques is to use several 2D X-ray views to create a 3D volumetric representation of the thorax. Clinicians will gain a better understanding of spatial connections within the thoracic cavity as a result, which will be especially helpful for lung pathologies, tumor localization, and surgical planning. Recent developments in deep learning and 3D vision have given rise to Neural Radiance Fields (NeRFs) — deep neural networks that learn to encode 3D scenes from multiple 2D images. A variant specifically designed for the medical imaging setting, called MedNeRF (Medical Neural Radiance Fields), is utilized in this work. MedNeRF is made suitable for medical imaging settings and can learn the volumetric shape of the thorax from multiple X-ray views. NeRFs learn by optimizing a neural network to produce color and density values along rays intersecting a scene. For medicine, this enables the model to encode intricate internal structures such as ribs, lungs, and heart tissues into a coherent 3D model.

Keywords— Chest Radiography, X-ray Imaging, Medical Imaging, Neural Rendering, 3D Volume Reconstruction, 2D-to-3D Conversion, Deep Learning in Radiology, Computer Vision in Healthcare, Neural Implicit Representations, Volumetric Medical Data, AI in Diagnostic Imaging, Image-based Reconstruction, Clinical Imaging Analysis

INTRODUCTION

Years have seen the imaging industry advance to a level that has transformed the way medical practitioners diagnose and manage diseases. Of the procedures employed in imaging, X-ray imaging is one of the most used tools because it is non-invasive and offers very useful information about a patient's status. CXR in particular are involved in the diagnosis and follow-up of thoracic diseases from pneumonia to cancer of the lung. Nonetheless, in spite of advancements in medical imaging technology, there exist restraints in interpreting 2D CXR. These restraints tend to cause difficulties in attempts to make accurate diagnoses. To proceed beyond these restraints researchers and physicians directed their focus towards view 3D reconstruction methods as a viable method, for enhancing diagnostics precision and in due course improving patient care.

The thorax is an area of the body that is important in terms of containing vital organs such as the heart and lungs, and as such, for imaging it is also crucial. CXR have been the standard for both imaging and analysis because they can capture and analyze information in a two-dimensional format, but it is limited, given that there lacks depth perception, structures overlap, and we can have difficulty distinguishing between pieces of different tissues that are on top of each other. Therefore, this can result in missing diagnoses, delayed treatment, and increased healthcare costs.

These limitations in conventional 3D reconstruction techniques are presently being alleviated through the development of multi-view technologies. By combining multiple views of the X-ray obtained at different angles using advanced computational algorithms, a comprehensive three-dimensional image of the thorax can be reconstructed. Not only does this sophisticated reconstruction preserve depth information but also allows for the discrimination between overlapping structures, thereby ensuring a better and more accurate assessment of thoracic anatomy and disease.

Join me on an important journey to explore the potential of multi-view 3D reconstruction to improve the diagnosis of thoracic diseases from CXR images. We'll begin with an exploration into the history of CXR imaging to better contextualize this new approach.

LITERATURE REVIEW

New 3D X-ray imaging methods that integrate multiple views are revolutionizing medical imaging. The technology is of enormous potential in transforming the diagnosis and treatment of diseases. However, if it is to be successfully integrated into daily clinical practice, some hurdles need to be addressed. The table below shows a comprehensive review of the past decade's research studies, highlighting these limitations that need to be addressed.

TABLE I: COMPARISON OF METHODS AVAILABLE THE LITERATURE

Citation	Author	Year	Methods/models	Limitations	Dataset used
Error! Reference source not found.	J. Ni et al.	2022	DenseNet-121 includes four AvgPool layers and 120 convolutions. To allow deeper layers to make effective use of features gathered at lower levels, this model disperses weights across every single layer, including dense blocks and transition layers.	The sensitivity of the proposed method to imperfections and noise in CXR images is a significant concern because lower quality images may lead to lower accuracy.	224,316 chest imaging photos labeled with 14 prevalent diseases from CheXpert and 377,110 chest imaging photos labeled with 14 prevalent diseases from MIMIC-CXR-JPG.
Error! Reference source not found.	Khan, Usman et al.	2018	• Iterative Closest Point (ICP): The point-to-point registration method decreases the distance between two images' matching points. •Volumetric Fusion: This method produces a single volume by combining multiple images in one.	It is extremely difficult to determine which of the methods presented in this paper are usable for applications since it does not examine the computational difficulty of the	Used several datasets including data from the NIST Digital Imaging and Remote Sensing Laboratory (DIRS), the Medical Imaging and Analysis Laboratory (MIAL), and FE

			• Surface Reconstruction: This method employs a volume to create a surface model. • Multi-view Stereo: This method produces a 3D depiction with the aid of many photographs of an object.	methods (hopefully the remark regarding computational difficulty was clear enough), and it does not provide information about how each method can be applied in context of the application.	
Error! Reference source not found.	Koehler et al.	2010	The Iterative Closest Point (ICP) method generates a 3D representation of the rib cage by first applying a coarse-to-fine geometric model to the CXR images.	The ICP method is computationally and temporally expensive, and it is sensitive to noise and artifacts.	a random sample of 10,000 chest X-ray images with a diagnosis of "pneumothorax" obtained from MIMIC-CXR-JPG and CheXpert.
Error! Reference source not found.	Corona-Figueroa, Abril et al.	2022	The Transformer-based Generative Adversarial Network or TRCT-GAN, utilizes natural language processing (NLP) techniques to find the association between biplanar CT and X-ray images. The generator is the model component responsible for providing fake CT images while the discriminator separates the real CT images from the fake ones. The 3D reconstruction phase will take place after the model has been built through training.	The model requires biplanar CT and X-ray images from a large dataset. Such dataset is not easy to get since it could be expensive and time-consuming. The model is under construction and is still improved upon. Furthermore, the model has not undergone clinical validation, which reflects how well the model could work in practice.	The extensive publicly available LIDC-IDRI dataset included CT scans from 1,018 lung cancer patients.
Error! Reference source not found.	Wang, Yufeng ; Sun, Zhan Li ; Zeng, Zhigang et al.	2023	X-ray to CT Generative Adversarial Network (X2CT-GAN) is based on a standard CNN architecture. The CNN has the ability to learn the spatial correlations between the	• The model may not be well generalized to other datasets because it may be biased for the specific dataset it was trained from.	The LIDC-IDပါထ -IDRI Multi-Modal collection contains 2D Lung X-ray images and 3D CT scans.

			pixels within the biplane X-ray images for CT reconstruction. The GANs part is then the same as the TRCT-GAN. The CNN-based architecture is more computationally efficient. This is the key difference.	• The quality of the biplanar CXR images can factor into the model. The model may not faithfully reproduce accurate CT images if the bi-planar CXR images are noisy or contain artifacts.	
Error! Reference source not found.	Shiode, Ryoya et al.	2019	U-Nets are a variation of a CNN architecture that is effective in tasks like image segmentation and reconstruction. The U-Net has an encoder path that associates features from the input image followed by a decoder path that reconstructs the output image using the features that were set aside in the encoder path. The U-Net is organized symmetrically. Encoder path: Input image Convolutional layers Max pooling layers Decoder path: Up-sampling layers Convolutional layers Output image	•Bones overlapping:19 we might not want to separate the radius from ulna in X-ray images because they overlap. •Presence of metal implants: The XR images may have artifacts from implanted metal in the wrist. CNNs are sensitive to artifacts and XR image noise. Thus, inaccurate reconstruction may arise from this.	Sourced particularly for this research. 105 x-ray images, 173 CT images containing a multimodal dataset.
Error! Reference source not found.	Y. Gao et al.	2021	The Spine Reconstruction CNN-Transformer (SRCT) design is employed by 3DSRNet, a generative adversarial network (GAN) design. In order to extract long-range interactions within the spine structure, the SRCT design employs a transformer.	It's in question whether 3DSRNet can be used with larger data sets, because it's based on a small data set of 1,000 x-ray pictures and spine models. Even though it was trained on data	The segmentation benchmark for multi-detector CT images has 374 CT scans from 355 patients and has precise centroid and voxel level annotations.

			Additionally, a CNN is employed in the Spine Reconstruction Texture (SRTE) system to understand the texture characteristics of the spine. These systems collaborate to enable the reconstruction of 3D spine models from 2D X-ray images to be easier.	that pertained to many spine disorders, it may not be able to accurately assess individual patient situations, particularly those with complex or unusual spinal problems.	
Error! Reference source not found.	Maken, Payal & Gupta, Abhishek.	2023	• CNNs are powerful AI models designed particularly f or image processing tasks. CNNs can recover 3D models of the internal structures by learning the features from X-ray images. •are a powerful artificial intelligence instrument that ge nerates data that is realistic. By translating 3D models to X-ray images or generating X-ray images from 3D models, GANs open up new possibiliti es for data analysis and manipulation. •Statistical shape models (SSMs) are mathematical tools for describi ng and assessing the shape of an object. SSMs can be utilized to reconstruct 3D anatomical models from X-ray images in the application of medical imaging. This enables scientists to disce rn the true shape of the anatomy in three dimensions	• Training Data Requirements: In many cases, a significant amount of data is required to train the model used to perform 2D-to-3D reconstruction, which may be difficult and expensive to acquire. • Noise Sensitivity: The noise present in the original X-ray images may also affect 2D-to-3D reconstruction, sometimes resulting in inaccurate reconstructions. • Ambiguity: The problem of recreating 3D images from a collection of 2D X-rays is an ambiguous problem. There may be multiple 3D reconstructions that satisfy the same collection of images, but it is hard to	The dataset is from the NIST Digital Imaging and Remote Sensing Laboratory (DIRS).

			by aligning the SSM with the X-ray images. • Triangular-surfaced representations are referred to as mesh-based models. 3D models can be generated from X-ray scans using techniques like volume reconstruction, which creates the model from the scanned object's 3D volume, and surface reconstruction, which constructs the model's surface from the X-ray data.	identify the one that is the most accurate given the ambiguity.	
Error! Reference source not found.	Dong, Xianling et al.	2015	An MV-SIR model runs with a CNN, based on the ResNet model. The CNN processes three separate images of a lung nodule: axial, coronal and sagittal. It also utilizes a second input, which is a 2D image of the region of the nodule. The second input is generated using a simple algorithm developed to segment the nodule region from the CT scans. This secondary input serves as a guide for the model to properly segment the nodule of interest.	• Sensitivity to image quality – The MV-SIR model is very sensitive to the input CT image quality. If the images have noise or blur, the model may not accurately partition lung nodules. • Computing cost – it is computationally expensive to train and run the MV-SIR model. It is a deep learning model, which requires extensive computing capacity.	The collection includes 600 chest CT scans with 1,900 lung nodules. The authors used this project in the development and evaluation of their MV-SIR model. They created two parts of the dataset: 200 CT images for testing and 400 CT images for training.
Error! Reference source not found.	Hosseinian, S. and Arefi, H.	2023	• Mathematical techniques known as statistical shape models (SSMs) are employed to describe and analyze an object's form. SSMs can be employed to model 3D anatomical models from X-ray	• Quality of the input: CXR images that are noisy or grainy could yield inaccurate reconstructions of the underlying anatomy.	The Medical Imaging and Analysis Laboratory (MIAL) dataset includes CT and MR images of various regions of the body (head, neck, chest,

			images for medical imaging purposes. This enables researchers to find the true shape of the anatomy in three dimensions using the SSM and comparing it to X-ray images. Deformable models are flexible 3D representations that can be adjusted to accommodate different datasets. Several X-ray images can be utilized to design 3D anatomical models with these models. This is done by distorting the model until it aligns with the X-ray data. • Atlas-based strategies: These methods utilize a pre-existing atlas that possesses complete anatomical information. In the process of recreating a three-dimensional replica of an anatomical feature from multiple X-ray images, this atlas serves as a reference. •Voxel-based methods: These methods segment the visual area into tiny cubes referred to as voxels. Subsequently, a label is assigned to each voxel, facilitating the construction of a three-dimensional representation of the object.	• Complexity of anatomy: Some anatomy (for example overlapping organs or complex structures) lend themselves more easily to accurate reconstruction than others.	abdomen, and pelvis). SpineWeb includes 3D models of the spine, and multi-angle chest X-ray images from individuals with spinal disorders.

DISCUSSION AND FINDINGS

The studies reviewed allude to an increasing focus on filling the gap between 2D imaging techniques such as CXR and volumetric 3D anatomical reconstructions with the help of computer vision and artificial intelligence. Various approaches, from the conventional geometric methods to deep learning-driven generative models, have been investigated with varying strengths and weaknesses.

1. Traditional Geometric Approaches: Research works such as [2] and [3] use methods like Iterative Closest Point (ICP) and Volumetric Fusion that are based on aligning and fusing multiple views. Although they provide interpretability and reasonable spatial accuracy, they are time-consuming computationally and noisy/artifact-prone in CXR images. Additionally, they tend to generalize poorly across datasets with diverse anatomical complexities or acquisition conditions.

2. CNN and Transformer-Based Approaches: Higher-order deep learning models, including DenseNet-121 [1], U-Net [6], and CNN-Transformer hybrids [7], possess great promise in feature extraction and anatomical localization. They are capable of learning spatial patterns and provide greater robustness than geometric techniques. Nevertheless, they usually require large annotated databases, are data-sensitive, and overfit when training with small or unbalanced datasets.

3. Generative Adversarial Networks (GANs): Various GAN-based models, to include X2CT-GAN [5], TRCT-GAN [4], and 3DSRNet [7], found initial promise for producing a realistic CT-like volume from biplanar CXR images. These models utilize feedback from the discriminators to improve generation quality, but often suffer from instability in training, limitations in training data, and lack of clinical validation. While CNN-GAN hybrids such as X2CT-GAN have computational efficiency that makes them more reasonable for use, the same dataset bias and sensitivity to noise are still limiting concerns.

4. Shape and Atlas-Based Reconstruction: Shape-based modeling [8,10], including Statistical Shape Models (SSMs), deformable models, and voxel-based segmentation methods provide anatomically-constrained and explainable and intuitive reconstructions. They are less well suited to generate accurate pathological or abnormal cases, and reference prior statistical models or atlases that describe the types of anatomical variations of interest while describing population-level differences in shape.

5. Dataset Variability and Utilization: A large number of studies draw upon existing datasets like CheXpert, MIMIC-CXR-JPG, and LIDC-IDRI, allowing them access to large-scale, annotated chest imaging data. Yet, the absence of paired X-ray and CT scans is a big challenge for supervised 2D-to-3D reconstruction tasks. A few studies utilize synthetic data or address limited pathologies (e.g., pneumothorax, spine diseases), which restricts generalizability.

6. MedNeRF – A Neural Rendering Method: The use of Medical Neural Radiance Fields (MedNeRF) offers a new solution by modeling the thoracic structure implicitly as a 3D radiance field. In comparison to explicit voxel-based or surface-based approaches, MedNeRF:

Learned continuous 3D representations from sparse 2D views.

Provides enhanced detail preservation, particularly for internal anatomy.

Accommodates easily to novel viewpoints and noise via neural generalization.

It still needs, though: Multi-view CXR inputs, which are not always provided in typical clinical settings.

Increased training time because of optimization of volumetric rendering.

CONCLUSION

In summary, the conversion of 2D chest X-rays to 3D anatomical representations is a monumental step forward in improving diagnostic imaging and patient-specific care. Existing literature demonstrates that while geometric methods have provided a starting point for developing techniques, state-of-the-art deep learning, generative models, and neural implicit representations such as MedNeRF, are superior, more flexible, and have the ability to understand detailed constituent parts of anatomy or important structures.

MedNeRF is particularly noteworthy as an efficient, detail-preserving method for performing maximal maximum thoracic reconstruction utilizing neural radiance fields (and allowing the clinician to view the chest anatomy from multiple novel perspectives). Methodologies such as these allow the clinician to perform better localization of disease and better scrutiny of risk factors, thereby increasing the possibility of good or improved outcomes both in the context of radiological characterisation and surgical planning.

Despite these advantages, MedNeRF - and the majority of the models reviewed - have several limitations, including:

Reliance on multi-view data (not often available in routine practice for CXR;

Vulnerability to imaging noise and artefacts;

Clinical validation for adoption into the health care landscape.

FUTURE WORK

To maximize the clinical value of 3D reconstruction from CXR images, some research directions are suggested:

1. Multi-View Data Collection and Standardization: Establish protocols for acquiring standardized multi-view CXRs as part of standard exams. Employ synthetic data augmentation or simulation (e.g., through GANs) to fill in the data gap when multi-view inputs are unavailable.

2. Hybrid and Explainable Models: Integrate MedNeRF with anatomical priors or statistical shape models (SSMs) for anatomical accuracy and interpretability improvement. Develop explainable AI (XAI) mechanisms in neural rendering frameworks for transparency in clinical application.

3. Real-Time and Low-Resource Optimization: Prioritize speeding up MedNeRF training and inference with lightweight architectures or hardware acceleration (e.g., tensor cores, pruning). Guarantee feasibility in low-resource health settings through model compression and knowledge distillation.

4. Clinical Validation and Deployment: Perform reader studies and clinical trials to compare 3D outputs generated by MedNeRF to standard-of-care CT/MRI. Develop end-to-end integrated diagnostic platforms that integrate 3D visualizations, radiologist reports, lesion tracking, and quantitative metrics.

5. Generalization and Robustness: Increase data coverage over age, sex, pathology, and imaging hardware to enhance generalization. Implement domain adaptation methods to render models robust across various hospitals or imaging modalities.

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