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Advancements in Orthopedic Surgery Planning: A Comprehensive Review of 3D Reconstruction from 2D X-rays

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Abstract

Orthopedic imaging demands precision for effective diagnosis, surgical planning, and monitoring of musculoskeletal ailments. X-ray imaging, while readily available and efficient, primarily offers 2D views, which can be insufficient for complex orthopedic procedures. Compared to the detailed 3D reconstructions provided by MRI and CT scans, X-rays have limitations. However, considering the cost of MRIs and radiation risks associated with CT scans, researchers are actively developing methods to derive 3D information from conventional X-rays. This paper provides a thorough analysis of diverse methodologies used for X-ray to 3D model generation. It examines the principles, prerequisites, and categories of these reconstruction techniques, alongside their applications, advantages, and disadvantages. We evaluate the accuracy of these methods, offering guidance to researchers working within this dynamic field.

Keywords
Orthopedic, Surgery, Planning, Diagnosis

1. Introduction
Clinical practice relies on various imaging modalities for diagnostic and surgical applications. In orthopedics, where precision is essential, imaging is vital for accurate diagnosis, pre-operative planning, and postoperative assessment (Cresson et al., 2010).

Although many imaging modalities exist, traditional X-rays remain a cornerstone of orthopedics due to their accessibility, low cost, and rapid results (Gupta et al., 2015). Table 1 compares the three most common imaging modalities used in orthopedics (Gupta et al., 2015).

Table 1. Comparison of three common imaging modalities used in orthopedics

Feature	X-ray	CT scan	MRI scan
Technology	Uses ionizing radiation to create 2D images of bones and some soft tissues.	Uses multiple X-rays to create detailed cross-sectional images of bones, soft tissues, and blood vessels	Uses strong magnetic fields and radio waves to create detailed images of organs, soft tissues, and bones
Image	2D	3D	3D
Availability	Widely available	Readily available in most hospitals	Less available than X-ray or CT scan
Radiation Exposure	Yes	Yes, but higher than X-ray	No
Cost	Low	Moderate	High
Advantages	Fast, inexpensive, good for visualizing fractures and dislocations	Excellent for visualizing internal injuries, fractures, and blood vessel abnormalities	Excellent for visualizing soft tissues, muscles, ligaments, and cartilage
Disadvantages	Limited to 2D images, poor for visualizing soft tissues	High radiation exposure, not ideal for pregnant women or children	Expensive, time-consuming, claustrophobic for some patients
Common orthopedic uses	Fractures, dislocations, joint problems, arthritis	Spinal injuries, complex fractures, internal injuries, tumor evaluation	Ligament tears, muscle injuries, cartilage damage, meniscal tears

While valuable as an initial diagnostic tool, the 2D nature of X-rays creates challenges for surgeons who must mentally visualize 3D anatomies (Gupta et al., 2016). This limitation is a critical hurdle in pre-operative planning, where precise bone geometry and joint relationships are needed (Neelapu et al., 2017). X-ray to 3D model generation addresses this, transforming X-rays into detailed virtual models and revolutionizing orthopedic surgical planning (Neelapu et al., 2017). Here's how:

- Enhanced Visualization - 3D models provide a depth of understanding that 2D X-rays simply cannot match. Surgeons can rotate, zoom in, and manipulate the models, gaining a comprehensive view of the anatomy. This improves their spatial awareness and allows them to visualize complex relationships between bones, joints, and soft tissues (Trivitron, 2024).

- Precise Preoperative Planning - 3D models facilitate accurate planning of surgical technique and implant placement. Surgeons can simulate procedures, design custom surgical guides, and anticipate complications.
- Improved Accuracy and Efficiency - 3D reconstructions can reduce surgical time by enabling better planning and minimizing the need for intraoperative adjustments. They can also lead to more accurate implant placement, reducing the risk of complications and the need for revision surgery (Trivitron, 2024).
- Personalized Medicine - 3D models allow for patient-specific treatment. Implants can be customized to perfectly fit the patient's anatomy, leading to better outcomes and faster recovery times.
- Education and Training - 3D models are powerful training tools, offering surgeons the ability to practice complex reconstructions in a virtual setting (Trivitron, 2024).

Researchers are actively developing innovative ways of generating 3D models from X-rays (Goswami & Misra, 2015). Our paper explores this dynamic field in detail.

2. Background

Orthopedic imaging is vital for diagnosis, pre-operative planning, and patient monitoring. X-rays hold a long-standing advantage due to their accessibility, cost-effectiveness, and speediness. However, their 2D nature complicates intricate orthopedic procedures. In contrast, MRI and CT scans offer detailed 3D reconstructions for better visualization of complex anatomy. However, their accessibility is limited by factors like cost and radiation exposure. In regions like Zimbabwe, where CT scans are often unavailable, the demand for alternative methods to generate 3D visualizations from X-rays is particularly high.

2.1 Problem statement

The central challenge lies in bridging the gap between the 2D limitations of X-rays and the need for precise 3D information for orthopedic surgical planning. How can accurate 3D models be generated from X-ray images while maintaining affordability and minimal radiation exposure?

2.2 Objective

This review aims to:
Provide a comprehensive overview of 3D reconstruction techniques from 2D X-rays, including traditional and deep learning-based methods.

2.3 Justification

This research is critical for addressing a significant gap in orthopedic surgical planning. By unlocking 3D insights from conventional X-rays, we improve patient care with cost-effective tools. Additionally, this work aids in developing accessible medical imaging around the globe.

3. Literature Survey

The field of 3D model generation from X-ray images is rapidly evolving, with researchers exploring a variety of methods ranging from straightforward analysis techniques to intricate statistical shape modeling (SSM) approaches (Goswami & Misra, 2015). Simple methods extract the bone's outline from calibrated images, projecting it backwards to estimate 3D shape. In contrast, SSMs are developed through the analysis of multiple 3D bone scans. They reveal common shapes and variations, serving as an 'average' bone template with adaptable variations. This average shape can be deformed using SSM guidance until its 2D projection matches the patient's X-ray, providing a considerably more accurate 3D reconstruction. While SSM-based methods are superior, they necessitate extensive bone morphology databases, potentially categorized by age, gender, and ethnicity for added accuracy (Goswami & Misra, 2015).

The following are some notable examples:
Galibarov et al. (2010) introduced a technique to generate customized models of the proximal femur using standard pre-operative X-rays. Their approach involved three primary steps: 1) employing an active contour algorithm to delineate the femur outline within the X-ray, 2) identifying the most similar 3D model from a pre-existing library, and 3) fine-tuning the selected model to closely match the extracted contour. This method prioritizes speed, automation,

and minimal image requirements. The accuracy of the reconstructed models was compared to models generated from CT scans, and the results were similar. This method is useful for situations where 3D data is not available.

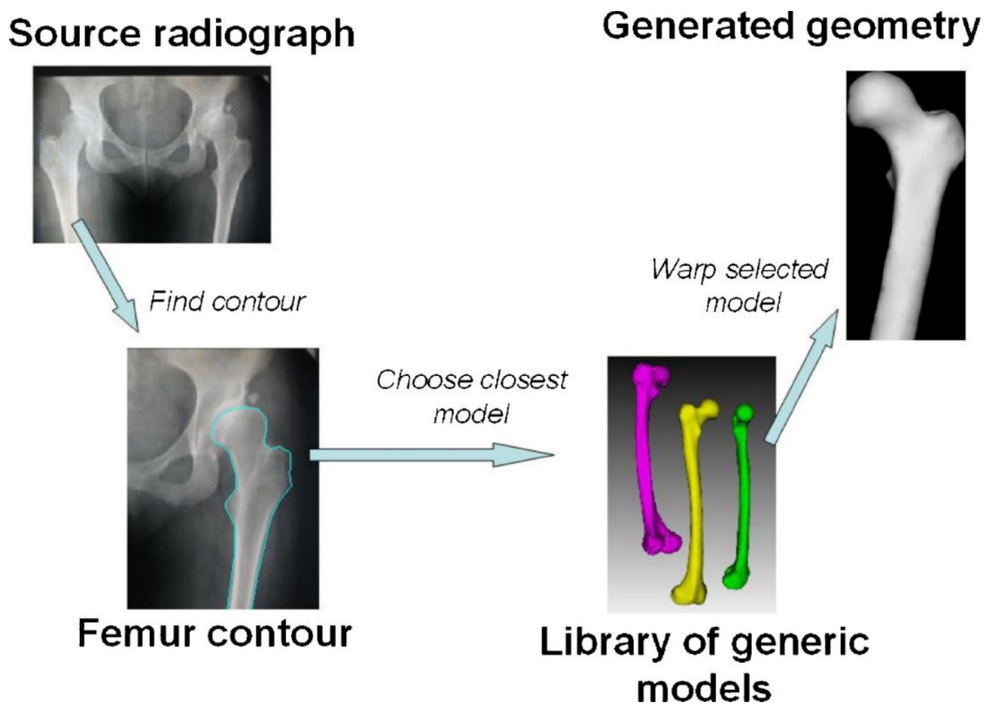

Figure 1. Galibarov et al. (2010) Method for 3D femur reconstruction from planar X-ray

Steffen et al. (2013) developed a method for accurate acetabulum shape reconstruction using a two-stage Statistical Shape Model (SSM) approach. They first create an SSM representing the entire hemi-pelvis from CT scans. Then, a specialized "patch-SSM" is generated by focusing on the acetabular region of the mean hemi-pelvis model. This hierarchical system allows initial user interaction for region definition, followed by automatic fine-tuning of the reconstruction process (Figure 1).

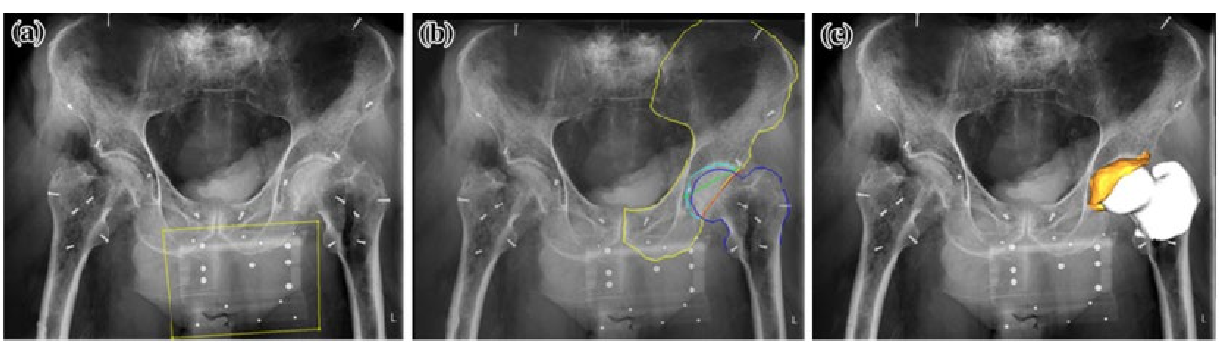

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Figure 2. Illustration of the 2D/3D hip joint generation workflow: (a) Initial X-ray image with a defined region of interest; (b Contours highlighting anatomical structures: hemi-pelvis (yellow), proximal femur (blue), acetabular rim (green/red), acetabular fossa (cyan); (c) Resulting 3D models of the acetabulum and proximal femur. (Adapted from: Steffen et al., 2013)

Laporte et al. (2003) proposed a technique for enhancing the precision of 3D anatomical models generated from X-rays. Their method begins with a preliminary 3D model, which could be derived from established reconstruction techniques. The model is segmented into anatomical regions, and these regions are used to locate analogous 2D contours within the X-rays. By projecting the 3D model onto the X-ray view, corresponding 3D contours are created. These contours are compared to the manually identified 2D contours, and the initial 3D model is iteratively optimized by adjusting its position, orientation, and size to minimize the distance between the two sets of contours. Finally, a mathematical technique called kriging is used to smoothly deform the optimized model, further refining its shape to closely match the X-ray data (Figure 2).

Similar to other approaches, Murat et al. (2007) introduced a computational method for 3D bone reconstruction. Their approach employs a standardized 3D template representing a typical bone shape. This template undergoes scaling and deformation until its 2D projection closely resembles the input X-ray image. The hierarchical freeform deformation technique facilitates these adjustments. To determine the optimal 3D bone shape, the method solves a series of optimization problems aimed at minimizing the difference between the input X-ray and the deformed template's projection. Sequential quadratic programming (SQP) is the algorithm used to tackle this complex optimization task.
In recent times with the advent of sophisticated machine learning algorithms, deep learning has been used to varying degrees to solve this challenge of 2D/3D registration. Rather than relying on traditional statistical models to represent individual bone shapes, Kasten et al. (2020) created a deep neural network that learns the overall patterns present in bone shapes directly from images. They cleverly trained their model using both supervised and unsupervised methods with DRR images (simulated X-rays from CT scans). To make the model work for real X-rays, they used style transfer. Their solution is groundbreaking because it efficiently creates accurate 3D reconstructions from just two X-ray images.

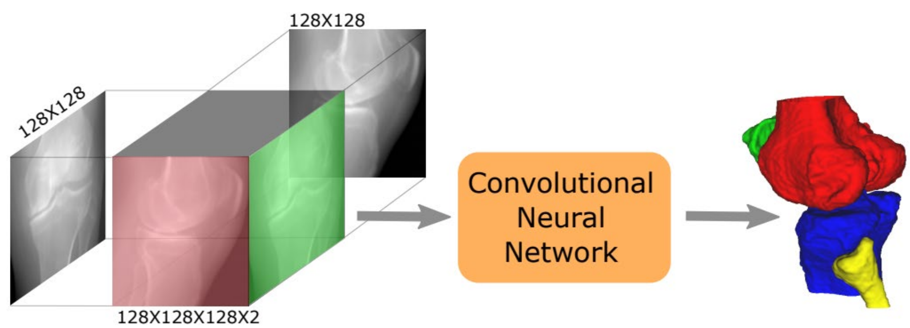

Figure 3. Schematic representation of the method: AP and lateral knee X-rays are transformed into a multi-channel 3D array. A CNN generates a 3D segmentation map of bone classes, enabling subsequent 3D bone reconstruction. (Adapted from: Kasten et al., 2020)

Shen et al. (2019) developed a multi-level neural network designed to reconstruct CT images from sparse X-ray projections. At its core, the network features a module that transforms features between 2D and 3D spaces. This transformation is key to the network's ability to bridge the dimensionality gap, permitting the transformation of a basic 2D projection into a volumetric 3D CT image (Figure 3 and Figure 4).

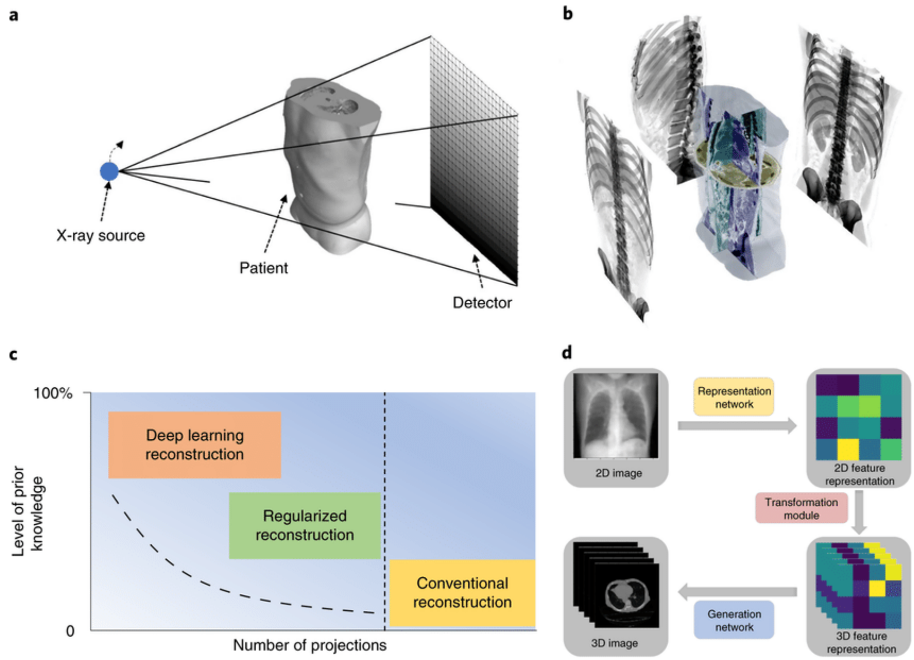

Figure 4. Illustrates the principles and potential of 3D image generation from limited X-ray data (a): Depicts the geometric setup of a CT system, including the X-ray source, patient, and detector. (b): Shows X-ray projections of a patient captured from three distinct angles. (c): Highlights various image reconstruction techniques in relation to prior knowledge and data sampling. (d): Demonstrates deep learning's ability to reconstruct volumetric images from single or multiple 2D projections. (Adapted from: Shen et al., 2019).

4. Discussion

The current landscape of 3D generation from 2D X-rays showcases a fascinating interplay between traditional and innovative deep learning methodologies. While traditional approaches like Statistical Shape Models (SSMs) provide valuable insights into bone morphology, they face limitations in adapting to individual patient anatomy and require large training datasets. Deep learning techniques, however, offer an exciting paradigm shift.

Neural networks trained on X-ray images demonstrate the capability to predict 3D bone shapes with remarkable accuracy, even from a single projection view (Kasten et al., 2020; Shen et al., 2019). Their ability to learn complex patterns directly from the data reduces the reliance on handcrafted features and predefined models. Particularly intriguing is the use of hierarchical architectures and feature-space transformations that bridge the dimensionality gap between 2D and 3D representations (Shen et al., 2019).

Several factors influence the quality and reliability of 3D reconstructions. Algorithmic complexity, the dataset's size and diversity, and the number of X-ray views used all have a significant impact. It's encouraging to see that ongoing research addresses these aspects, paving the way for more robust and clinically practical solutions.

The most promising applications of 3D reconstructions from X-rays lie within the orthopedic domain. Potential benefits include enhanced 3D visualization, meticulous preoperative planning, patient-specific surgical guides, and personalized implants. These advancements have the potential to revolutionize surgical outcomes, reduce procedural time, and support surgeons in making more informed decisions.

While deep learning methods in 3D reconstruction exhibit remarkable potential, certain challenges and areas for further research remain:

- **Dataset Generalizability:** The accuracy of deep learning models depends heavily on the diversity and size of the training datasets. Addressing biases and ensuring generalizability across different patient populations, imaging equipment, and anatomical variations is crucial.

- **Explainability:** Understanding the internal decision-making processes of neural networks remains an important issue. Increasing the interpretability and transparency of deep learning models can build trust and facilitate their integration into clinical workflows.
- **Ground Truth Validation:** In many cases, ground truth 3D data (usually CT scans) is necessary to train and validate deep learning models. Exploring methods for reliable 3D reconstruction in the absence of such ground truth data is an essential avenue for further research.

5. Conclusion

This review highlights the impressive advancements achieved in constructing 3D models from X-ray images. Traditional and deep learning approaches offer complementary strengths, and further research into their integration holds immense potential. The accessibility and cost-effectiveness of X-rays, paired with sophisticated reconstruction techniques, can bridge crucial gaps in orthopedic care, particularly in settings where advanced imaging resources may be limited.

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Biographies

Dr. Lindelwe Ncube brings a background of six years in medical practice to their current research in biomedical engineering. After earning an MBChB from the University of Zimbabwe, he is now pursuing a master's under Professor Tawanda Mushiri. Their work focuses on merging clinical practice with technological advancements through the development of a technique to produce 3D printable models of anatomical fractures using standard X-rays.

Professor Tawanda Mushiri is a leading expert in Artificial Intelligence, Medical Robotics, and Biomedical Engineering. His groundbreaking research focuses on developing Robotic First Aid (RFA) systems to reduce fatalities from road traffic accidents and applying AI for disease prediction modeling. With a patent pending for in-vehicle RFA, Prof. Mushiri spearheads AI initiatives at the University of Zimbabwe and has secured funding exceeding USD$3.5 million for his impactful work. As Coordinator and Associate Professor in the Department of Biomedical Informatics and Biomedical Engineering, Prof. Mushiri demonstrates a profound commitment to student mentorship. He holds memberships in the Zimbabwe Institute of Engineers and the Engineering Council of Zimbabwe, actively contributing to industry standards. Prof. Mushiri's extensive publication record includes books, book chapters, journal articles, and conference proceedings. He supervises at both graduate and postgraduate levels globally and serves as an external examiner for respected institutions. Prof. Mushiri holds a Senior Research Associate Research Fellowship at UJ and provides expertise as a consultant Biomedical Engineer, ensuring the optimal functionality of vital medical equipment.

Charles Mbohwa Professor Charles Mbohwa is a Distinguished Professor in Energy and Sustainability Engineering at the College of Science, Engineering and Technology at the University of South Africa. He was, previously the University of Zimbabwe Pro-Vice Chancellor responsible for Strategic Partnerships and Industrialisation from 1st July 2019 up to 30th June 2022. Before that he was a professor of sustainability engineering in the Faculty of Engineering and the Built Environment at the University of Johannesburg. He was a mechanical engineer in the National Railways of Zimbabwe from 1986 to 1991, and lecturer and senior lecturer at the University of Zimbabwe. He was Senior Lecturer, Associate Professor and Full Professor at the University of Johannesburg. He was Chairman and Head of Department of Mechanical Engineering at the University of Zimbabwe from 1994 to 1997; Vice-Dean of Postgraduate Studies Research and Innovation in the Faculty of Engineering and the Built Environment at the University of Johannesburg from July 2014 to June 2017 and Acting Executive Dean in the Faculty of Engineering and the Built Environment from November 2017 to July 2018. He has published very widely. He holds a BSc Honours in Mechanical Engineering from the University of Zimbabwe in 1986; Master of Science in Operations Management and Manufacturing Systems from University of Nottingham 1992; and a Doctor of Engineering from the Tokyo Metropolitan Institute of Technology 2004.