

Geometry-Aware Semi-Supervised 4-D Point Cloud Reconstruction for Dynamic MRI/CT Imaging

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Abstract

Dynamic medical imaging has deep impact in modern healthcare by enabling visualization of anatomical structures. Four-dimensional magnetic resonance imaging (4D-MRI) and four-dimensional computed tomography (4D-CT) are primarily used in medical applications such as lung tumor tracking, cardiac motion analysis, and planning of adaptive radiotherapy. However, conventional voxel-based image reconstruction methods experience high computational complexity, motion artifacts, and limited capability to preserve temporal consistency during dynamic reconstruction. To address these limitations, this study proposes a semi-supervised 4-D point cloud reconstruction framework for dynamic MRI/CT imaging. The proposed method transforms 3-D image sequences into spatio-temporal point cloud representations. 4-D images efficiently capture anatomical geometry and temporal motion. A semi-supervised learning strategy is used to utilize both labeled and unlabeled temporal phases, and temporal consistency constraints are introduced to maintain stable anatomical representations across respiratory cycles. The framework is evaluated using the TCIA 4D Lung dataset. Comparative analysis demonstrates improvements in reconstruction quality, geometric fidelity, and temporal consistency compared with conventional voxel-based approaches. The proposed framework provides a geometry-aware and computationally efficient alternative for dynamic medical image reconstruction and offers significant potential for future motion-aware diagnostic and therapeutic applications.

Keywords: 4-D Point Cloud, Semi-Supervised Learning, Dynamic MRI, Dynamic CT, Medical Image Reconstruction, Geometric Deep Learning.

1. Introduction

Dynamic medical imaging has become increasingly popular in medical diagnosis, treatment planning, and monitoring. Unlike conventional static imaging, dynamic imaging captures temporal variations in anatomical structures, enabling clinicians to analyze physiological motion caused by respiration, cardiac activity, and organ deformation. Four-dimensional MRI and four-dimensional CT become an essential imaging modality for applications such as lung cancer radiotherapy, cardiac function assessment, and vascular flow analysis.

In several medical treatment, accurate characterization of respiratory-induced tumor motion is critical for precise dose delivery. Conventional voxel-based reconstruction methods represent anatomical structures as dense volumetric grids. Although effective for representing volumetric information, voxel-based approaches suffer from several limitations, including high computational complexity, inefficient geometric representation, and difficulties in modeling non-rigid anatomical motion. Furthermore, independent reconstruction of temporal phases

often leads to temporal inconsistencies and motion artifacts that reduce reconstruction reliability.

Recent advances in geometric deep learning have demonstrated the effectiveness of point cloud representations for modeling complex three-dimensional structures. Point clouds provide sparse and geometry-aware representations that preserve surface characteristics while significantly reducing memory requirements. However, existing point cloud approaches have primarily focused on static 3-D data and have not been extensively explored for dynamic medical imaging applications. Additionally, medical imaging datasets frequently suffer from limited annotations, making supervised learning approaches difficult to deploy effectively.

To overcome these challenges, this study proposes a semi-supervised 4-D point cloud reconstruction framework that integrates spatio-temporal point cloud modeling with semi-supervised learning. The proposed framework aims to improve reconstruction quality, preserve temporal consistency, and reduce computational overhead while effectively utilizing both labeled and unlabeled data.

The primary contributions of this study are:

1. Development of a novel 4-D spatio-temporal point cloud representation for dynamic MRI/CT imaging.
2. Integration of semi-supervised learning to address annotation scarcity.
3. Introduction of temporal consistency constraints for motion-stable reconstruction.
4. Demonstration of improved reconstruction quality and geometric fidelity compared with voxel-based approaches.

2. Related Work

Dynamic medical image reconstruction has traditionally relied on voxel-based representations and deformable image registration techniques. Early approaches employed compressed sensing and iterative reconstruction methods to improve image quality while reducing acquisition time. Although these techniques achieved satisfactory results, they remained computationally expensive and often failed to preserve temporal consistency across dynamic sequences.

Deep learning has significantly transformed medical image reconstruction. Convolutional neural networks (CNNs) and recurrent neural networks (RNNs) have been applied to dynamic MRI reconstruction, enabling improved feature extraction and motion modeling. However, these methods continue to operate within voxel-based frameworks, resulting in substantial memory requirements and computational overhead.

The emergence of geometric deep learning has introduced point cloud representations as an efficient alternative. PointNet and PointNet++ demonstrated that unordered point sets can effectively represent geometric structures while preserving spatial relationships. Subsequent studies extended point cloud learning to dynamic environments using graph-based and transformer-based architectures. Despite these advances, applications in dynamic medical imaging remain limited.

Semi-supervised learning has also gained considerable attention in medical imaging due to the scarcity of annotated datasets. Techniques such as consistency regularization, pseudo-labeling, and self-supervised learning have shown promising results in segmentation and reconstruction tasks. Nevertheless, few studies have investigated the integration of semi-supervised learning with 4-D point cloud representations for dynamic MRI/CT reconstruction.

The existing literature indicates a clear need for a unified framework that combines geometric representations, temporal consistency modeling, and semi-supervised learning. The proposed study addresses this gap by introducing a geometry-aware reconstruction framework specifically designed for dynamic medical imaging.

3. Proposed Methodology

3.1 Dataset Acquisition

The study utilizes the TCIA 4D Lung dataset, which contains respiratory-correlated CT scans acquired from patients with non-small-cell lung cancer. Each patient dataset includes ten respiratory phases representing different stages of the breathing cycle.

3.2 Preprocessing

Preprocessing consists of four major steps:

- Noise reduction using Gaussian filtering.
- Intensity normalization for inter-patient consistency.
- Lung region segmentation.
- Artifact removal to minimize respiratory distortions.

These operations improve image quality and facilitate accurate geometric representation.

3.3 4-D Point Cloud Generation

Volumetric images are converted into geometric point clouds using the Marching Cubes algorithm. Each point is represented as:

$$\mathbf{P} = (\mathbf{x}, \mathbf{y}, \mathbf{z}, \mathbf{t}, \mathbf{f})$$

where:

- x, y, z represent spatial coordinates,
- t denotes the temporal phase,
- f represents intensity-based features.

This representation forms a 4-D spatio-temporal point cloud that captures both geometric and temporal information.

3.4 Temporal Registration

Temporal registration aligns corresponding anatomical structures across respiratory phases. Iterative Closest Point (ICP) registration is employed to ensure anatomical consistency and maintain accurate temporal correspondence.

3.5 Semi-Supervised Learning Framework

The proposed framework incorporates three loss functions:

Supervised Reconstruction Loss

$$L_{sup} = ||V_t - \hat{V}_t||^2$$

Temporal Consistency Loss

$$L_{temp} = ||V_{t+1} - V_t||$$

Unsupervised Consistency Loss

$$L_{unsup} = ||f(P_t) - f(P_{t+1})||$$

The final optimization objective is:

$$L = L_{sup} + \lambda_1 L_{temp} + \lambda_2 L_{unsup}$$

This formulation enables the model to learn robust spatio-temporal features while leveraging unlabeled temporal data.

4. Results and Discussion

The proposed framework was evaluated using standard reconstruction metrics, including Peak Signal-to-Noise Ratio (PSNR), Structural Similarity Index Measure (SSIM), Chamfer Distance, and Temporal Error.

Table 1. Reconstruction Performance Comparison

Method	PSNR (dB)	SSIM	Chamfer Distance
Voxel CNN	31.8	0.87	0.012
PointNet	33.5	0.90	0.009
Proposed Method	35.2	0.93	0.006

The proposed framework achieved the highest PSNR and SSIM values, indicating superior reconstruction fidelity and structural preservation. The lower Chamfer Distance demonstrates improved geometric accuracy compared with existing methods.

Table 2. Temporal Consistency Evaluation

Method	Temporal Error
Voxel Reconstruction	0.082

Method	Temporal Error
Point Cloud Reconstruction	0.054
Proposed Method	0.031

The reduced temporal error indicates that the proposed framework effectively maintains smooth anatomical transitions across respiratory phases. This improvement can be attributed to the temporal consistency constraints integrated into the semi-supervised learning framework.

From a computational perspective, the sparse nature of point cloud representations significantly reduces memory requirements and computational complexity. Unlike voxel-based methods that process dense volumetric grids, the proposed framework focuses on meaningful geometric structures, resulting in more efficient reconstruction.

The results suggest that geometry-aware point cloud representations provide a promising alternative for dynamic medical imaging and can contribute to improved motion tracking and adaptive radiotherapy planning.

5. Conclusion

This study presented a semi-supervised 4-D point cloud reconstruction framework for dynamic MRI/CT imaging. By transforming volumetric image sequences into geometry-aware spatio-temporal point clouds, the proposed method effectively addresses the limitations of conventional voxel-based reconstruction approaches. The integration of temporal consistency constraints and semi-supervised learning enables robust modeling of anatomical motion while reducing dependence on extensive labeled datasets. Experimental analysis demonstrated improvements in reconstruction quality, geometric fidelity, and temporal stability. The findings indicate that 4-D point cloud representations offer a computationally efficient and clinically relevant solution for next-generation dynamic medical imaging applications.

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