Semi-Supervised 4-D Point Cloud Reconstruction for Motion-Consistent Dynamic MRI/CT Imaging

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Abstract

Dynamic medical imaging techniques, such as four-dimensional magnetic resonance imaging (4D-MRI) and four-dimensional computed tomography (4D-CT), are used in applications such as lung tumor tracking, cardiac motion analysis and vascular flow modeling and allow physicians to visualize the motion of organs over time. However, the conventional voxel-based reconstruction techniques are computationally intensive and they fail to provide the accurate description of temporal correspondence and geometric features in dynamic medical images.

This research introduces a semiautomatic 4-D point cloud reconstruction system of dynamic MRI/CT images. The proposed solution incorporates semi-supervised deep learning to utilize the identified and the labels of temporal frames as well as transforms volumetric medical images into the form of spatio-temporal point clouds. Temporal consistency requirements are used to maintain anatomical stability during respiratory stages. Experiments on the TCIA 4D Lung dataset reveal that when compared to voxel-based reconstruction methods, the reconstruction accuracy, geometric fidelity and temporal consistency are improved. It has been found that efficient geometry-based medical image reconstruction framework is provided by point-cloud-based representations.

KeyWord: 4-D point cloud, image reconstruction, semi-supervise learning, MRI scan.

1. Introduction

Dynamic medical imaging is requisite in modern clinical diagnosis and therapy planning. For analyzing the motions of the organs that occur due to breathing or heartbeat, technologies, such as 4-D CT and 4-D MRI, can assist medical workers by recording their anatomy in multiple time intervals.

Motion in respiration makes it difficult to determine where the tumor is in the planning of radiation of lung cancer. Four-dimensional imaging allows visualizing tumor mobility during breathing cycles and makes motion-sensitive radiation therapy and more accurate treatment planning possible.

Despite these benefits, conventional reconstruction techniques rely on voxel-based representations, which have several drawbacks:

• A high level of computational complexity

• Ineffective anatomical geometry depiction
• Capturing non-rigid temporal deformation is challenging.

Voxel-based techniques ignore the geometric structure of anatomical surfaces, treating medical pictures as dense grids. As a result, many methods find it difficult to effectively depict dynamic motion. Point cloud representations offer an effective means of modeling complicated forms and deformable structures, as recent developments in geometric deep learning have shown. Point clouds, compared to voxel grids, use sparse geometric points to represent surfaces, which makes dynamic anatomy modeling more effective.

Nevertheless, there are still a lot of use of point cloud representations in dynamic medical imaging. Research on creating temporally consistent 4-D point clouds from MRI data is still ongoing.

To surpass this difficulty, a semi-supervised framework for reconstructing dynamic medical pictures as spatiotemporal point clouds is presented in this research.

2. Problem Statement

Voxel-based techniques that are computationally costly and lack geometric efficiency are a major component of traditional 4-D MRI analysis. Voxel grids can depict volumetric structures, although they frequently fall short of maintaining the geometric properties of anatomical surfaces.

Although point cloud representations are lightweight and geometry-aware, it is still difficult to create temporally consistent 4-D point clouds from dynamic medical imaging data.

Among the main obstacles are:

• Variation between time frames
• MRI/CT scans are not independent of noise
• Scarcity of supervised datasets for model training

For clinical applications like motion tracking and flow analysis, these difficulties helps in developing of a reliable pipeline that can transform dynamic medical pictures into temporally consistent point cloud representations.

3. Research Gap

Several research gaps exist in current medical imaging reconstruction techniques:

1. **Lack of standardized datasets**
   Only a small number of databases offer MRI pictures along with matching point cloud annotations.

2. **Voxel-centric analysis**
   Instead of using geometric representations, the majority of reconstruction methods now in use rely on voxel representations.

3. **Poor temporal correspondence modeling**
   Accurate tracking of anatomical features across time is necessary for dynamic imaging.

4. **Error propagation from MRI artifacts**
   Reconstructed geometric representations may be affected by noise and image artifacts.

5. **Limited clinical integration**
   Clinical imaging workflows rarely incorporate point-cloud-based deep learning techniques.

4. Methodology

The proposed framework consists of five major stages:

4.1 Acquisition of Data

4-D point clouds are created using dynamic MRI or CT scan datasets. The TCIA 4D Lung dataset, which includes imaging data from lung cancer patients throughout many respiratory phases is used for this study.

Each dataset of similar form includes

1. Various stages of breathing
2. Volumetric CT scans
3. Motion patterns unique to each patient

4.2 Pre-processing

Pre-processing is a crucial step in any DL based study, following are the various steps to be taken while pre – processing a dataset.

4.2.1 Filtering out noise

One of the most important pre-processing steps is filtering noise, which entails lowering random fluctuations and undesired signals found in unprocessed medical images. The imaging device, outside interference, and patient movement during scanning are only a few of the sources of noise. Effective noise filtering is useful in identifying and extracting similar anatomical features accurately and enhances the contrast and clarity of the image. In order to minimize noise, but still have considerable edges and patterns in the image, such methods as median filtering, Gaussian smoothing, or simpler methods such as non-local means filtering are typically employed.

4.2.2 Normalization of intensity

Scaling the strengths of the voxels across the dataset to a standard scale or distribution is called normalization of intensity. Normalization ensures uniformity in multiple images and patients since raw medical images may exhibit a significant range of discrepancy in intensity values as a result of differences in scanner conditions, patient physiology, or image acquisition. The frequent techniques that are applied in such a process are z-score normalization, histogram equalization and min-max normalizing. Normalization also enhances the reliability of segmentation, surface extraction and the successive analysis of the results by standardizing the intensity values which ultimately increases the reliability and comparability of reconstructions.

The lung regions are segmented according to the 3D geometry of the lung.

Segmentation of the lung areas is done in order to clearly isolate the lung anatomy and the rest of the tissues and structures present in the imaging data. The key point about this stage is that it becomes possible to focus the attention on the pulmonary areas, which are often the target of the research conducted about lung diseases and the monitoring of tumors. Segmentation may be done by various methods, including threshold-based methods, region-growing algorithms or more advanced deep learning models that have been trained to detect lung borders. The quality, creation and analysis of the point cloud are further improved by reducing the interference of the adjacent organs such as the heart, the bones or other thoracic organs hence also precise segmentation can be required.

4.2.4 Elimination of artifacts

Distortions and anomalies, which confuse the anatomical features or artifacts should be eradicated. The artifacts in medical imaging may be the movement of the patient or technical limitations and issues related to capture of the image like beam-hardening effects, ghosting, or streaking. These artifacts may obscure or distort the anatomical features of interest that might lead to errors in subsequent procedures during reconstruction. The process of detecting and reducing these distortions by the application of particular noise -filtering methods, correction algorithms, or post-processing methods can be referred to as artifact elimination. This way we will make sure that the data by which we do our geometric reconstruction is a good representation of the anatomy of the patient. This useful artifact elimination improves the precision and decreases the reliability of the obtained models. Those processes ensure that the data provided can be used to do the geometric reconstruction.

4.3 Point Cloud Generation

Surface extraction algorithms like the Marching Cubes convert the volumetric images to geometric point clouds.

Each point is being represented as following

[(x, y, z, t, f)]

where,

x, y, z	=	spatial coordinates
t	=	Temporal phase
f	=	Voxel intensity or feature value

This representation gives us a **4-D spatio-temporal point cloud**.

4.4 Temporal Registration

Temporal registration is the alignment of anatomical features during respiratory stages. which we maintain records of the time stamp of the pictures that shall be utilized in the future in the generation. point clouds. It is in this phase that spatial relationships between related anatomical are ensured places will never change.

4.5 Deep Learning Analysis

Spatio-temporal learning is performed on a semi-supervised neural network architecture attributes of the point cloud sequences. Three loss functions are included in the model.

Supervised loss

Lsup=||Vt−V^t||2L_{sup} = ||V_t - \hat{V}_t||^2Lsup=||Vt−V^t||2

Temporal consistency loss

Ltemp=||Vt+1−Vt||L_{temp} = ||V_{t+1} - V_t||Ltemp=||Vt+1−Vt||

Unsupervised consistency loss

Lunsup = ||f(Pt)−f(Pt+1)||L_{ unsup} = ||f(P_t) - f(P_{t+1})|| Lunsup =||f(Pt)−f(Pt+1)||

Final objective function

L=Lsup+λ1Ltemp+λ2LunsupL = L_{sup} + \lambda_1 L_{temp} + \lambda_2 L_{unsup } L= Lsup +λ1 Ltemp +λ2 Lunsup

5. Results

Qualitative Analysis

Method	PSNR	SSSIM	Chamfer

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 semi-supervised point cloud reconstruction algorithm had the highest performance in all metrics of evaluation..

Temporal Consistency

Method	Temporal Error
Voxel Reconstruction	0.082
Point Cloud	0.054
Proposed Method	0.031

The results are stating improved temporal stability is seen in reconstructed anatomical structures.

6. Clinical Significance

The proposed semi-supervised 4-D point cloud reconstruction method has significant clinical implications of enhancing medical imaging and therapy practice. The process significantly enhances the abilities of clinicians to visualize and analyze the movements of organs over a period of time since it provides more precise and temporally stable images of dynamic anatomic structures. This is important in such applications as vascular flow, cardiac motion and lung tumor motion. Traditional voxel-based reconstruction methods are typically susceptible to the geometric complexity of deformable tissues and are subject to noise and artifacts, both of which may be detrimental to the accuracy of diagnosis and treatment. The point cloud-based method, alternatively, offers a lightweight geometrical-aware alternative that increases the realism of dynamic models without compromising complex surface geometries. It also leads to better localization of tumors and other pathological characteristics, and therefore interventions such as radiotherapy can be planned more accurately. There is a necessity to understand the minute motions of tumors during respiratory cycles in order to achieve maximum treatment efficiency and minimal damage to healthy tissue. Moreover, the improved temporal consistency of the reconstructed models provides medical workers with a more reliable understanding of the organ mechanics and deformation patterns that can be used to better track the progression of the disease and response to the treatment. This modeling and visualization innovation is useful in the development of the motion-sensitive diagnostic equipment, enhance flexible radiotherapy applications, and pave the way to more personalized treatment regimes. This method can potentially decrease uncertainty, improve treatment outcomes, and eventually deliver a better patient care in case it is introduced into the clinical workflows. Moreover, it is a practice that can be extended to the broader clinical application, because of its capacity to apply semi-supervised learning with minimal structured information. This will make it possible to scale the complex dynamic imaging analysis to encompass a range of medical environments and patients, which would translate into the promotion of precision medicine, and less invasive therapies. These advancements could lead to more accurate surveillance and planning of tumors and cysts in terms of their treatment protocols.

7. Conclusion

To overcome the problems of traditional voxel-based approaches this research paper proposes a novel semi-supervised 4-D point cloud reconstruction model to be used in dynamic medical imaging. The proposed method is effective to represent the complex deformations and motions of anatomical structures through time, by transforming volumetric MRI and CT data into sparse and geometry-sensitive point clouds. This resolves the old problems of geometric fidelity and computing costs. This framework implements a semi-supervised approach with a deep learning strategy to learn strong spatial-temporal features by combining the multiple loss functions- supervised, temporal consistency and unsupervised, to ensure that the reconstructed point clouds are consistent in anatomy across respiratory or cardiac cycles.

Critical performance measures such as PSNR, SSIM, and Chamher distance, experimental achieved results with the TCIA 4D Lung dataset demonstrate that this algorithmology significantly outperforms the traditional voxel based methods and existing point cloud algorithms. The method is distinguished by its great temporal stability that is important in proper motion tracking and clinical judgment. The large reduction in the temporal error indicates that the reconstructed dynamic models are more effective in preserving the anatomical connections through time to allow superior progostic and diagnostic uses.

The benefit of densely gridding voxels with sparsely gridding point clouds has several significant clinical benefits. These involve higher reconstruction accuracy resulting into a higher accuracy in motion analysis and alignment of tumor when performing vital procedures such as radiation therapy planning. Also, the geometric clarity of point clouds enables diagnosis in real-time and motion sensitivity to enhance the visualization of anatomical surfaces and deformations in real-time. Such developments provide the possibility to introduce advanced techniques of reconstruction into the general treatment process, which ultimately results in the more accurate and customized treatment strategies.

In due course this research presents a host of new possibilities in the research of 4D point clouds and their measurement. More so, we can extend such a system to full-range MRI data, with implicit neural representations to even more accurate reconstructions, and test the procedure on large-scale clinical trials. It is also mobile, the system that is almost real-time reconstructive would be of great use in clinical cases. All said and done, this paper shows the massive potential of geometry-sensitive, semi-supervised learning-based point cloud reconstruction to change the dynamic medical imaging and offers an avenue to more accurate, effective, and patient-centered prognosis and diagnosis.

8. Future Work

Through the assistance of the three-dimensional and four-dimensional dynamic imaging analysis, future studies on this field are intended to enhance the existing model, rendering it to be applicable to the entire MRI data. Implicit neural representations, including neural radiance fields or similar algorithms, can be used to generate reconstructed models in a way that is better resolved and better detailed, with a reduced computing overhead. Clinical validation is also an important step to assess the strength, accuracy and generality of the proposed method to a diverse range of patient groups and imaging scenarios. Also in future, real-time reconstruction skills, which facilitate timely clinical decision-making and dynamic patient monitoring during treatments should be developed. Such advances would significantly improve the adaptive therapy planning and intraoperative navigation. Also a more detailed insight into disease processes could be gained by the analysis of the combination of semi-supervised reconstruction of point clouds with other state-of-the-art methods and data which include functional imaging or genetic data. Collectively these future directions assists in the maximization of clinical importance of dynamic medical imaging, enhancement of surgery and therapy, and expedite the implementation of the latest imaging technologies in routine medical practice.

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Page 9 of 10 - Integrity Submission Submission ID trn:oid:::16158:124457013

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