Review of Deep Learning-Based 4D Image Construction on Point Cloud for MRI

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Current words require high quality medical images, especially in MRI as MRI is used for vital diagnostic tools. MRI is used to provide very high-quality images of organs and tissues inside the body. It helps to diagnosis a wide variety of conditions from Tron ligament to tumors, also used to examine brain hart and spinal cord. However current MRI scanning techniques can only provide either 2D or 3D representation of the images. At the time of treatment of the disease's detection of dynamic nature of physiological condition is very hard. To solve this issue recent research has explored 4D imaging techniques. This adds time dimension to volumetric data to better understand organ motion, particularly in cardiac and respiratory applications. This review study analysis and presents the current advancements in deep learning-based 4D image construction using point cloud representations for MRI. Point clouds offer a sparse and flexible geometric format suitable for motion-rich imaging tasks. The study covers various deep learning models including PointNet, graph neural networks, recurrent networks, and transformer-based architectures that have been employed for processing spatiotemporal point cloud data. The study concludes with insights into potential future directions.

Keywords: 4D Medical Imaging, Deep Learning, Point Cloud, MRI Reconstruction, Image Denoising,

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Introduction

Magnetic Resonance Imaging (MRI) is one of the most widely used non-invasive imaging techniques in modern medicine. MRI is used to scan high quality images of tissues and organs and provide detailed anatomical visualization. MRI is one of the useful diagnostic tools in neurological disorders, musculoskeletal issues, cardiovascular diseases and cancer. As traditional MRI scan 2D or 3 D images. These images are not able to represent dynamic physiological process such as cardiac motion, blood flow. Recently, the idea of four-dimensional (4D) imaging, which adds the time dimension to 3D volumetric data, has gained considerable interest. 4D imaging allows clinicians to observe structural and functional changes in real time. This capability lets them capture complex dynamics such as heart movement, breathing patterns, and brain functions. This improvement opens new avenues for accurate disease detection and better treatment strategies. However, obtaining high-quality 4D MRI data is both resource-intensive and time-consuming, emphasizing the need for innovative methods to speed up and reconstruct dynamic volumetric imaging.

A promising approach to address these challenges is the use of point clouds to represent 3D data. Unlike voxel-based or grid-based models, point clouds directly depict the spatial arrangement of sampled points in 3D space. This method provides a flexible and memory-efficient way to model complex anatomical structures. This flexibility is particularly important for dynamic MRI, where accurately representing and reconstructing time-changing 3D structures is crucial.

At the same time, rapid advancements in deep learning have transformed the field of medical imaging. Neural networks have proven effective in recognizing patterns in high-dimensional medical data, including image classification, segmentation, reconstruction, and denoising. Deep learning architectures designed for point cloud analysis, like PointNet and its variations, offer strong methods for directly learning spatial and temporal relationships from 3D geometric information. Combining these advancements with MRI reconstruction could significantly improve 4D imaging speed, reduce artifacts, and enhance diagnostic accuracy.

Review of Literature

Recent foundations for 4-D (time-resolved) MRI is relevant to point-based cloud analysis come from 4D-flow MRI, which acquires volumetric, time-varying velocity fields of blood along with anatomy. The 2023 JCMR consensus update codified acquisition options, post-processing workflows, QA/validation standards, and publication checklists—critical prerequisites because spatial/temporal resolution, noise, and bias directly propagate into any downstream surface/point sampling and flow-on-surface analysis [1], [2].

A complementary body of work addresses dynamic MR reconstruction and super-resolution to improve the fidelity of time-resolved volumes prior to surface/point extraction. In 4D-flow specifically, 4DFlowNet introduced a deep residual network that super-resolves low-resolution vector fields using CFD-derived supervision, demonstrating improved agreement in phantoms and in vivo and motivating learned sampling before geometric sampling [3]. Subsequent studies explored post-processing CNNs and temporal super-resolution for 4D-flow, reinforcing that reconstruction choices materially affect per-point velocity accuracy once data are transferred from voxels to sampled surfaces or center lines [4], [5].

Where volumetric time series are not directly available, slice-to-volume reconstruction (SVR) methods assemble isotropic 3-D (and 4-D) anatomy from motion-corrupted multi-stack 2-D acquisitions—especially vital in fetal MRI. Recent work focuses on clinically viable, automated SVR pipelines, implicit-representation SVR with self-supervised meta-learning, and scanner-integrated, real-time variants [6], [7].

Converting 4-D MRI volumes to point clouds generally follows a consistent pipeline: (i) per-frame segmentation of target anatomy (e.g., myocardium, aorta), (ii) surface extraction (e.g., marching cubes/mesh fitting) or centerline/skeleton generation, (iii) point sampling (uniform or Poisson-disk) with optional attributes like normals and 4D-flow vectors transferred from voxels, and (iv) temporal correspondence/registration to create coherent tracks across frames. The consensus guidance for 4D-flow explicitly informs sampling density and QA for velocity vectors attached to surface points (e.g., divergence, wall-shear stability), while dynamic registration choices (image-space optical flow versus point-space ICP/CPD) determine how stable inter-frame point identities are for downstream analyses [1].

On the learning side, a rapidly growing literature examines medical point-cloud shape learning across registration, reconstruction, and variation modeling. The 2025 survey by Zhang, Liang, and Wang synthesizes methods from 2021–2025, highlighting trends that are directly applicable to MRI-derived 4-D point clouds: (a) point-based backbones (PointNet/PointNet++, DGCNN) extended with temporal attention or recurrent modules; (b) point transformers/graph transformers that leverage self-attention for non-local spatiotemporal context; (c) hybrid representations combining voxel-space segmentation with point-space refinement; and (d) self-supervised and generative approaches (contrastive learning, autoencoders, diffusion) to mitigate label scarcity and complete noisy/partial surfaces [8].

Although much of the classical point-cloud literature originates outside medicine, several foundational architectures underpin medical adaptations. PointNet/PointNet++ introduced permutation-invariant set learning and hierarchical local feature aggregation [9]; DGCNN added dynamic edge-convolution to capture local topology [10]; and Point Transformer employed attention to model long-range dependencies—capabilities that translate well to cardiac motion and vessel flow patterns when extended across time. Medical surveys and applications commonly adapt these backbones with temporal modules to analyze 4-D wall motion, valvular dynamics, and flow-on-surface phenomena [8].The study found following contribution and gaps identified by different study.

Title & Authors	**Year**	**Contribution**	**Research Gap**
4D flow cardiovascular magnetic resonance consensus statement – Dyverfeldt et al.	2023	Provides standardized acquisition, quality control, and reporting guidelines for 4D flow MRI, ensuring reproducibility and clinical consistency.	Does not address point cloud representation or deep learning-based geometric modeling.
4DFlowNet: Super-resolution of 4D Flow MRI using deep learning – Ferdian et al.	2020	Introduces a CNN-based framework to enhance spatial and temporal resolution of 4D flow MRI velocity fields, improving quantitative flow metrics.	Limited to voxel-based enhancement; no conversion into surface/point-cloud for geometric learning.
Temporal super-resolution of 4D Flow MRI using deep neural networks – Fathi et al.	2022	Proposes deep models to interpolate temporal frames in 4D flow MRI, reducing scan time while maintaining temporal fidelity.	Focuses on temporal resolution, not on structural point-based representation.
Slice-to-volume reconstruction in fetal MRI using implicit neural representations – Hou et al.	2025	Uses implicit neural functions and meta-learning for motion-robust reconstruction of 3D/4D fetal MRI volumes.	High-quality volumes achieved, but no standardized pipeline for temporal point-cloud generation.

Fast slice-to-volume registration for motion correction in fetal MRI – Kainz et al.	2018	Presents efficient slice-to-volume registration (SVR) for motion correction in fetal MRI, improving clinical usability.	Classical approach; lacks integration with deep point-cloud learning or temporal consistency.
A Survey of Medical Point Cloud Shape Learning – Zhang, Liang & Wang	2025	Comprehensive survey of medical point-cloud learning in registration, reconstruction, and variation, including self-supervised and generative models.	Survey scope is broad; lacks dedicated focus on 4D MRI-derived point clouds.
PointNet: Deep learning on point sets for 3D classification and segmentation – Qi et al.	2017	Introduces the first deep architecture for unordered point sets, demonstrating robustness for 3D shape classification/segmentation.	Designed for static 3D; no temporal modeling for dynamic 4D MRI.
Dynamic Graph CNN for learning on point clouds – Wang et al.	2019	Employs edge-convolution to capture local geometric context, useful for shape dynamics and topology learning.	Not validated on medical or MRI-derived dynamic point clouds.
Point Transformer – Zhao et al.	2021	Applies self-attention to point sets, enabling long-range geometric feature learning for 3D tasks.	Method not explored for time-varying MRI point clouds or flow-attached attributes.

Research Gaps Identified

The field faces several key challenges: there is a lack of standardized, publicly available benchmark datasets that pair 4D MRI volumes with temporally registered point clouds for training and evaluation; research remains largely voxel-centric, with 4D MRI methods such as super-resolution, reconstruction, and temporal interpolation rarely extending to surface- or point-based geometric representations; existing point cloud architectures (e.g., PointNet, DGCNN, Point Transformer) are designed for static 3D shapes and provide limited support for temporal correspondence and dynamic point tracking; motion artifacts, undersampling, and reconstruction errors in MRI volumes propagate directly into derived point clouds, yet robust artifact-mitigation strategies are underexplored; despite consensus guidelines like those in 4D flow MRI, point-cloud deep learning is not integrated into clinical diagnostic workflows; interpretability and trustworthiness remain insufficiently addressed, hindering adoption in high-stakes settings; domain shift impairs generalization across scanners, vendors, field strengths, protocols, and patient populations; and current pipelines treat reconstruction, segmentation, surface extraction, and point learning as disjoint steps, highlighting the absence of an end-to-end framework that maps 4D MRI directly to point-cloud representations.

Conclusion

Across studies, several recurring challenges emerge. First, there is a lack of standardized benchmarks that pair time-resolved MRI volumes with temporally registered point-cloud ground truth, forcing many groups to derive point sets post-hoc from voxel labels and to rely on bespoke correspondence heuristics [8]. Second, error propagation from undersampled or motion-corrupted MRI (and from learned super-resolution) can degrade geometric and velocity accuracy at points—necessitating physics-aware smoothing (e.g., divergence control) and robust temporal alignment [3], [5]. Third, domain shift across scanners, field strengths, and protocols remains a barrier to generalization, motivating self-supervised pretraining and meta-learning (as seen in recent SVR work) and stronger QA practices borrowed from the 4D-flow consensus [2], [6]. Finally, clinical integration demands not only accuracy but also reliability, interpretability, and workflow fit—areas where consensus documents and clinically oriented SVR pipelines are beginning to close the gap [1], [7].

In summary, the literature shows that 4-D point-cloud MRI sits at the intersection of (i) robust dynamic MRI reconstruction (cine/4D-flow/SVR), (ii) careful surface/point sampling with temporal correspondence, and (iii) modern point-cloud learning adapted to medical constraints. With standards maturing on the MRI side and a new wave of medical point-cloud methods, the field is poised for end-to-end pipelines—from k-space/slices to temporally consistent, attribute-rich 4-D point sets—supported by community benchmarks and physics-aware training objectives [8].

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