LEX LOCALIS-JOURNAL OF LOCAL SELF-GOVERNMENT
ISSN:1581-5374 E-ISSN:1855-363X
VOL. 23, NO. S5(2025)

DEEP LEARNING FRAMEWORK FOR GLOBAL MOTION CORRECTION IN CINE CARDIAC MRI WITH EXPLICIT DISPLACEMENT FIELD ESTIMATION

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Abstract
Cardiac cine magnetic resonance imaging (CMR) is the clinical reference standard for assessing ventricular function, myocardial motion, and valvular abnormalities. However, its diagnostic reliability is often compromised by global motion artifacts, including translation, rotation, and contraction/expansion, which degrade frame-to-frame alignment and impair quantitative accuracy. Traditional correction strategies, such as ECG gating, breath-hold acquisitions, and retrospective registration, remain limited by patient compliance and sensitivity to irregular rhythms, motivating the need for advanced data-driven approaches.In this work, we present a deep learning framework for global motion correction in cine CMR that integrates dual displacement field estimation, a global motion transformation layer, and a hierarchical feature encoding–decoding network with frequency-domain channel attention. The model predicts bidirectional motion fields between moving and fixed frames, enforces temporal consistency, and explicitly corrects for cardiac-specific global displacements. Evaluation was performed on the **CMRxRecon2024 dataset**, comprising 180 cine CMR subjects with 12 motion states per scan. Experimental results demonstrate that the proposed method achieves a normalized root mean squared error (NRMSE) of **0.098**, outperforming the state-of-the-art Coarse-to-Fine Diffusion baseline (NRMSE = 0.1225). These findings confirm that explicitly modeling global cardiac motion within a diffusion-informed encoder–decoder architecture substantially improves reconstruction quality and temporal alignment. The proposed framework advances cine CMR motion correction and has the potential to enhance downstream clinical assessment of ventricular function and valvular pathology.

1 Introduction

Cardiac magnetic resonance imaging (CMR) is the clinical reference standard for quantifying ventricular function, myocardial dynamics, and valvular pathologies. Cine CMR provides high-resolution, time-resolved images across the cardiac cycle, enabling volumetric and functional assessment. However, temporal consistency in cine sequences is compromised by global cardiac motion, including translational shifts, rotational displacements, and myocardial contraction or expansion. These inter-frame variations introduce spatial misalignment that reduces image fidelity and impairs quantitative accuracy in downstream analysis, such as regurgitant volume (RVol) and regurgitant fraction (RFrac) estimation in aortic regurgitation assessment.Traditional motion mitigation strategies include electrocardiogram (ECG)-gated acquisitions, breath-hold protocols, and retrospective registration. ECG gating synchronizes acquisition with cardiac phases but is sensitive to arrhythmic variability, while breath-hold strategies reduce respiratory artifacts at the expense of patient compliance. Retrospective registration using affine or B-spline transformations can partially correct frame-to-frame displacement but performs suboptimally under large global motion and complex cardiac deformation. Consequently, conventional pipelines are limited in their ability to maintain anatomical consistency across cine frames [1]-[4].

Deep learning–based methods have recently advanced the state of motion artifact correction in MRI. Generative models, particularly diffusion probabilistic models, have demonstrated strong performance in reconstructing high-fidelity images from undersampled and motion-corrupted k-space. Diffusion-based motion-compensated reconstruction frameworks estimate displacement fields jointly with image restoration, thereby reducing temporal blurring and improving structural alignment. In parallel, unsupervised registration networks such as Global Motion Field Estimation Module (GMFEM) employ encoder–decoder architectures with spatial transformer layers to estimate dense deformation fields without ground-truth annotations, achieving accurate alignment of rigid and non-rigid motion [5].

Recent studies have also incorporated hierarchical and temporally-aware strategies. Coarse-to-fine (C2F) refinement schedules within diffusion models progressively correct large-scale global motion at early iterations, followed by local refinement of residual displacements. Spatio-temporal priors have been leveraged to exploit the periodicity of the cardiac cycle, ensuring stable corrections across dynamic sequences. Collectively, these approaches establish a technical foundation for motion correction frameworks that integrate generative modeling, deformation field estimation, and temporal consistency modeling to address global motion in cine CMR[6]-[8].

Although cine CMR provides dynamic visualization of the beating heart, its diagnostic utility is frequently degraded by motion artifacts arising from translation, rotation, and myocardial contraction or expansion [9][10]. Conventional correction strategies, such as ECG gating, breath-hold acquisitions, and retrospective registration, remain limited: they are sensitive to arrhythmias, dependent on patient compliance, and unable to robustly correct large inter-frame displacements. As a result, residual global motion leads to temporal misalignment across cine frames, reducing anatomical fidelity and impairing quantitative accuracy in downstream tasks such as ventricular volume estimation or regurgitant fraction analysisDiffusion-based methods have been investigated for motion correction in MRI under different settings. For rigid motion, the reconstruction problem has been formulated as joint posterior sampling over both the image and the associated motion parameters[11]. Extensions of diffusion models to blind inverse problems, where the forward operator is not explicitly defined but assumed to lie within a family of degradations such as shift-invariant blurring, have also been reported[12]. This framework has further been adapted to MRI applications, showing effectiveness in recovering images from motion-corrupted acquisitions[13]. Moreover, diffusion models defined on function spaces have been explored in video processing, where enforcing inter-frame consistency has proven beneficial, a concept that holds strong potential for dynamic MRI motion correction [14].Finite element digital image correlation (FE-DIC) [15] has been extended with an alternating correction framework that jointly updates motion fields and intensity estimates, achieving progressive refinement of registration across CEST sequences Unlike conventional FE-DIC methods that rely on strict intensity constancy, this approach integrates mechanical regularization to suppress non-physical deformations while simultaneously correcting for reference–target contrast differences, resulting in improved stability and accuracy. A model-based strategy for nonrigid motion correction has also been presented, addressing the dual challenges of motion representation and estimation [16]. Motion representation is achieved by adapting the nonuniform fast Fourier transform (NUFFT) into image-space gridding, enabling exact forward–adjoint operator pairs. Nonrigid SENSE operators are further introduced to embed motion directly within the multi-coil acquisition model. For motion estimation, low-resolution image-based navigators (iNAVs) and high-resolution self-navigating 3D iNAVs are employed. Data acquisition alternates between sparse high-resolution and complete low-resolution non-Cartesian trajectories per heartbeat, enabling respiratory-phase–resolved reconstructions and estimation of nonrigid respiratory motion.In a different line of work, JSMoCo [17] has been proposed to simultaneously estimate motion parameters and time-varying coil sensitivity maps from under-sampled MR acquisitions This joint recovery is highly ill-posed due to the enlarged solution space, but the use of score-based diffusion models as priors, together with MRI physics-based constraints, significantly improves reconstruction robustness. Motion is parameterized as rigid transformations with learnable variables, while coil sensitivity maps are modeled using polynomial functions. A Gibbs sampler ensures consistency between the estimated sensitivity maps and reconstructed images, preventing error propagation from pre-estimation steps.Another contribution in [18] focuses on cardiac T1 mapping, where a modified modality-independent neighborhood descriptor (mo-MIND) has been introduced as a registration metric robust to large contrast variations . To handle severe motion, a pre-deformation augmentation strategy is applied during training, and both are integrated into a Hierarchical Feature Encoding–Decoding Network (HFED-Net)–based registration network. This combination allows the model to maintain alignment accuracy even in the presence of substantial contrast shifts and motion.

1.1 Motivation and contributions

Accurate motion correction in cine CMR is essential for reliable quantification of cardiac function, particularly in conditions such as aortic regurgitation where precise frame alignment impacts the estimation of regurgitant fraction and ventricular volumes. Conventional approaches, including ECG gating, breath-holding, and retrospective registration, remain limited by patient compliance, arrhythmias, and poor performance under large displacements. These shortcomings reduce temporal consistency and compromise diagnostic accuracy. Recent advances in deep learning, especially diffusion-based reconstruction and learning-based registration, offer new opportunities to address global cardiac motion artifacts and enable more consistent and clinically reliable cine CMR analysis.This work makes the following key contributions:

1. **Cardiac-Specific Global Motion Correction:**

We introduce a deep learning–based framework tailored for cine cardiac MRI that explicitly estimates and corrects translational, rotational, and contraction/expansion motion, improving temporal consistency across dynamic frames.

2. **Dual Motion Field Estimation:**

A bidirectional displacement estimation strategy is implemented, ensuring consistency between moving-to-fixed and fixed-to-moving alignments. This design minimizes residual misalignment and enhances structural fidelity.

3. **Global Motion Transformation Layer:**

A dedicated module integrates global cardiac motion priors into the displacement field, addressing limitations of conventional nonrigid-only correction methods and achieving robust performance under large displacements.

4. **Hierarchical Feature Encoding–Decoding with Attention:**

The proposed architecture employs a Hierarchical Feature Encoding–Decoding Network (HFED-Net) with frequency-domain channel attention (FCA) to strengthen feature discrimination, enabling accurate recovery of subtle cardiac deformations.

5. **Comprehensive Evaluation on Cine CMR Data:**

Using the CMRxRecon2024 dataset, the model demonstrates a significant reduction in normalized root mean squared error (NRMSE = 0.098) compared to the state-of-the-art Coarse-to-Fine Diffusion baseline (NRMSE = 0.1225), confirming superior temporal alignment and motion correction performance.

2 Proposed methodology

The proposed CMR processing workflow involves a DL-based motion estimation step and a follow-up motion correction step, between Cardiac Motion Field (CMF) localization and tracking. The DL model trained was used during motion estimation on B-mode images derived from beamformed in-phase/quadrature (IQ) data without clutter filtering (Fig. 1). For every frame, the DL model produced a deformation field, which was applied to correct the corresponding CARDIAC MOTION FIELD (CMF) localization results. In benchmarking, the motion estimation phase can also be replaced with affine, two-stage, or Hierarchical Feature Encoding–Decoding Network (HFED-Net)-based DL approaches.Outside of the motion estimation and correction processes, the rest of the CMR pipeline was traditionally designed. First, a spatiotemporal filter based on singular value decomposition (SVD) was applied to the beamformed signals in order to suppress tissue clutter and noise. Single CARDIAC MOTION FIELD (CMF)s were then localized and detected by the radial symmetry (RS) algorithm, in which a 3 × 3-pixel window (one pixel per wavelength) was chosen to calculate the centroids of local maxima. The number of local maxima was limited to 3, and at most 90 particles per image were taken into account. CARDIAC MOTION FIELD (CMF) tracking was conducted with the Kuhn–Munkres assignment algorithm having a maximum allowable linking distance of 2 pixels and a minimum track length limited to 15 consecutive frames.Lastly, a microvascular density map of the spinal cord was obtained by summing up all CARDIAC MOTION FIELD (CMF) tracks per frame. Super-resolution imaging was obtained through reconstruction of the final images at a pixel size of 10 × 10 μm.

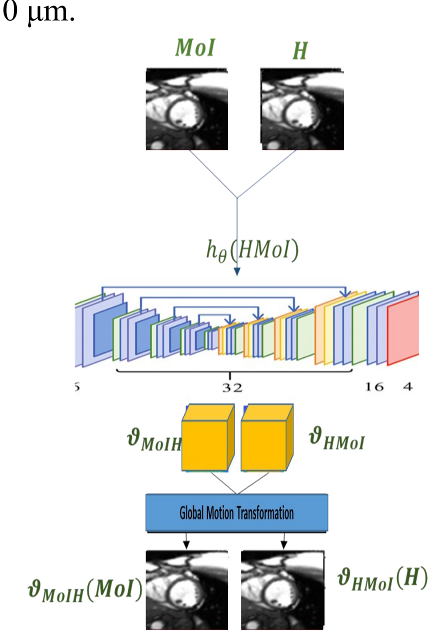


Figure 1 propsoed model

The proposed framework is designed to correct global motion artifacts in cine cardiac MRI by jointly estimating displacement fields and applying motion transformation to align dynamic cardiac frames. The model accepts two inputs: a **moving image (MoI)**, representing the motion-affected cine frame, and a **fixed image (H)**, representing the reference frame. These paired inputs are processed through a **deep encoder–decoder network** based on a hierarchical feature encoding–decoding structure with skip connections. This architecture enables the extraction of both local and global representations while preserving fine anatomical details across multiple scales.The encoder progressively downsamples the concatenated inputs, learning compact motion-aware feature representations. The decoder then upsamples these features to predict forward and backward deformation fields and which capture the global displacement between the moving and fixed frames. These dual motion fields allow for bidirectional consistency, ensuring that both the alignment of the moving image to the fixed image and the reverse transformation are explicitly modeled.

The estimated motion fields are applied using a **Global Motion Transformation layer**, which integrates translation, rotation, and contraction/expansion components into the deformation maps. This ensures that the corrected cine frames preserve temporal consistency and anatomical fidelity. The final outputs are the warped versions of the moving and fixed frames which represent globally aligned cine MRI frames suitable for subsequent reconstruction and quantitative analysis.By combining hierarchical feature extraction, dual-field estimation, and global motion transformation, the framework directly addresses the limitations of existing approaches, which either focus narrowly on non-rigid deformations or lack explicit modeling of cardiac-specific global motion. This makes the model particularly well-suited for enhancing cine cardiac MRI reconstruction quality and improving diagnostic accuracy in downstream clinical applications such as ventricular volume and regurgitant fraction analysis.

1.1 Deep Deformable Motion Correction Network (DDMC-Net)

The static images (H) and dynamic images (MoI) were merged to create two-channel inputs to the model network, and every two were a static and its associated dynamic image. Synthetic data, which were generated by using Field II, were used as fixed reference images in simulation experiments, and their deformed versions, which were generated using different deformation fields, were regarded as dynamic images. For in vivo experiments, for in network training, two randomly chosen frames from the same rat spinal cord were used as a fixed–moving image pair. The neural network denoted as $h_\theta(HMoI)$is used to predict the displacement fields ϑ_{HMoI} and ϑ_{MoIH} in between H and MoI , wherein θ denotes the network parameters. The outputs ϑ_{HMoI} and ϑ_{MoIH} is applied to the modified images through a GMT(**Global Motion Transformation) module** henceforth achieving motion correction.\

2.1 Neural network architecture design

The network employed in this study is based on a Hierarchical Feature Encoding–Decoding Network (HFED-Net) encoder–decoder architecture, where each encoder block includes two 3 × 3 convolutional layers with batch normalization (BN) and ReLU activations followed by 2 × 2 max-pooling, and each decoder block incorporates a 2 × 2 transposed convolutions (stride = 2) with two subsequent 3 × 3 convolutional layers with BN and ReLU. To enhance feature representation, a frequency-domain channel attention (FCA) module, inspired by frequency-domain techniques in image registration, is integrated into the framework, enabling spatial features from both encoder and decoder pathways to be transformed into the frequency domain for adaptive channel recalibration. This design strengthens the network's ability to capture subtle image displacements, and the final output layer applies a linear projection to generate a four-channel deformation field representation he axial and lateral displacement of ϑ_{HMoI} and ϑ_{MoIH} .

1.2 Loss function

In line with the Global Motion Field Estimation Module (GMFEM) framework, the loss function $N(.)$ for the deformation field estimated from fixed and moving images, is formulated as the sum of two components: an appearance similarity term $N_{sim}(.)$ and a smoothness regularization term $N_{smooth}(.)$.

$$N(.) = N_{sim}(.) + \alpha N_{smooth}(.)$$

Here, α denotes the regularization parameter, which in this study was set to 5 based on a grid search conducted over the range 1–10 with a step size of 1. This value provided the highest structural similarity index measure (SSIM) on the validation dataset. In conventional supervised algorithms, optimization is performed for each individual volume pair. By contrast, the Global Motion Field Estimation Module (GMFEM)-based approach models the deformation field as a parameterized function of the data, where the function parameters are optimized by minimizing the loss function across an entire dataset of volume pairs. Thus, instead of performing pair-specific optimization of deformation fields, the method achieves global optimization of the shared parameters of the function ϑ_{HMoI} and ϑ_{MoIH} .

The transformations between fixed (H) and moving (MoI) images are generally invertible within the image but may fail at the edges due to missing correspondences. To address this, both losses are jointly incorporated, enforcing bidirectional consistency. This design enhances accuracy, with the appearance difference loss defined accordingly:

$$N_{sim}(H, MoI, \boldsymbol{\vartheta}) = -(\boldsymbol{LCC}(\boldsymbol{H}, \vartheta_{MoIH}(MoI)) + \boldsymbol{LCC}(MoI, \vartheta_{HMoI}(H))$$

Wherein $\vartheta_{MoIH}(MoI)$ and $\vartheta_{HMoI}(H)$ denote MoI by ϑ_{MoIH} ,Local cross-correlation (LCC) is adopted as the similarity measure, where a higher LCC value reflects better alignment between images. For two images K and L, the LCC is computed as follows:

$$LCC(K,L) = \sum_{r \in \omega} \frac{\left(\sum_{r_k} (K(r_k) - K(r))(L(r_k) - L(r))\right)^2}{\sum_{r_k} (K(r_k) - K(r)^2) \sum_{r_k} (L(r_k) - L(r))^2}$$

Wherein ω denotes the domain of pixels in the image $K(r)$ and $L(r)$ within the local mean intensities K and L within a 9*9 local window wherein $K(r_k)$ and $L(r_k)$ denote the pixel values at location r_k iteration over a local window.

The smoothing loss penalizes abrupt local variations in the deformation field by enforcing spatial smoothness through a diffusion regularizer. It evaluates the consistency of displacement gradients in both forward (H to MoI) and backward (MoI to H) transformations. Spatial gradients are approximated using differences between neighboring voxels. This ensures smoother and more realistic deformation fields.

1.3 Motion Correction Methods

In the proposed method, the suggested Global Motion Field Estimation Module (GMFEM)-based deep learning technique was contrasted with three benchmark motion correction techniques: affine registration, two-stage motion estimation, and Hierarchical Feature Encoding–Decoding Network (HFED-Net)-based registration, the latter also being a DL-based method. Affine and two-stage applied compensation on B-mode images using single reference frames, whereas all methods compensated CARDIAC MOTION FIELD (CMF) localization results as well.

Severe registration addresses global translation and rotation using six degrees of freedom, and affine registration generalizes this by accounting for shear and scaling with 12 degrees of freedom. Two-stage registration fuses affine global motion estimation with B-spline–based nonrigid registration and provides local deformation modeling with a control point mesh. The resolution of the mesh controls degrees of freedom and computational complexity. Optimization is realized through the minimization of a loss function that integrates global similarity and local smoothness constraints, with the affine component being optimized first through multiresolution search followed by nonrigid refinement. Hierarchical Feature Encoding–Decoding Network (HFED-Net)-based registration predicts deformation fields directly from fixed–moving image pairs during training by minimizing mean square error against ground-truth fields.

$$N(\Xi, \omega) = -\mathrm{N}_{sim}(J_0, V(o) + \alpha N_{smooth}(V)$$

Where J_0 denotes the fixed ref image , MoI is the moving image V is the combined transformation, α is the weight parameter,n each stage, motion correction methods employed iterative gradient descent, terminating once a local optimum of the loss function was reached. Unlike conventional approaches that use a single fixed reference frame. At every step, motion correction algorithms used iterative gradient descent, stopping when a local optimum of the loss function was attained. In contrast to standard methods that utilize one fixed reference frame, this research, made use of multiple reference frames to better estimate the motion, with the transformations being estimated both intra- and inter-blocks of data and being applied to localized CARDIAC MOTION FIELD (CMF) locations.

3 Performance Evaluation

The proposed framework introduces a deep learning–based approach for global motion correction in cine cardiac MRI, explicitly addressing translational, rotational, and contraction/expansion displacements that compromise temporal consistency and quantitative accuracy. The model accepts paired cine frames (moving and fixed) and processes them through a hierarchical encoder–decoder backbone with skip connections, enhanced by a frequency-domain channel attention mechanism to capture motion-sensitive features. A Global Motion Field Estimation Module (GMFEM) predicts bidirectional displacement fields, while a Global Motion Transformation Layer (GMTL) applies these fields to generate aligned cine reconstructions. Training is guided by a composite loss function combining local cross-correlation for appearance similarity, smoothness regularization for physiologically plausible motion, and bidirectional consistency to minimize residual misalignment

3.1 Dataset Details

For this study, we utilized short-axis cardiac cine MRI data from the CMRxRecon2024 challenge[19]. The dataset consists of 180 subjects with fully sampled k-space acquisitions, of which 150 were allocated for training and 30 for evaluation. Training samples were generated using the first three temporal frames from the central slice of each subject, cropped in k-space to a resolution of 162 × 162, resulting in a total of 450 training images. For inference, Gaussian and uniform undersampling masks provided by the challenge organizers were applied, each with an acceleration factor of R = 24. Each cine scan includes 12 motion states, but it is important to note that these are acquired data without corresponding ground-truth motion fields.

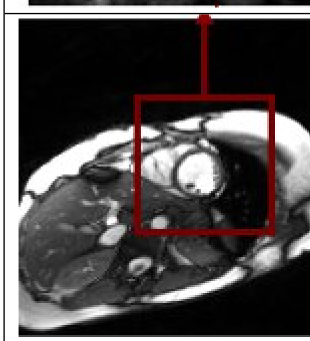
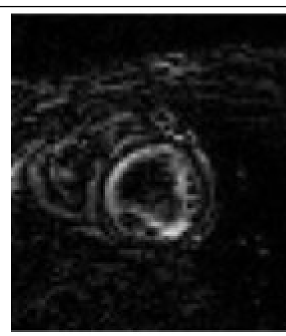
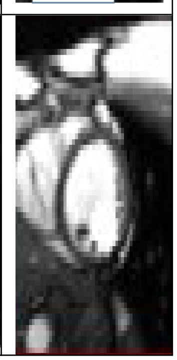
3.2 Results

Table 1 presents a quantitative comparison of motion correction performance between the proposed framework and existing reconstruction methods on the CMRxRecon2024 cine MRI

ISSN:1581-5374 E-ISSN:1855-363X
VOL. 23, NO. S5(2025)

dataset. Performance is evaluated using the **normalized root mean squared error (NRMSE)** metric, where lower values indicate better frame-to-frame alignment and reduced motion-induced distortion.The results demonstrate that conventional reconstruction techniques, such as **Bart PICS** and **DPS**, yield higher errors due to limited ability to explicitly correct for complex cardiac motion. The diffusion-based baseline, **C2F-Diffusion**, achieves improved performance (NRMSE = 0.1225), benefiting from its coarse-to-fine modeling of non-rigid displacements. However, the proposed framework further reduces reconstruction error, achieving an **NRMSE of 0.098**, which represents a substantial improvement over the state of the art. This confirms that explicitly integrating global motion priors and dual displacement field estimation enhances correction robustness and temporal consistency in cine cardiac MRI.

Table 1 comparison of proposed and existing model

GT(Ground_Truth)	Bart PICS	DPS	C2F-MC	PS (Proposed)
				
				

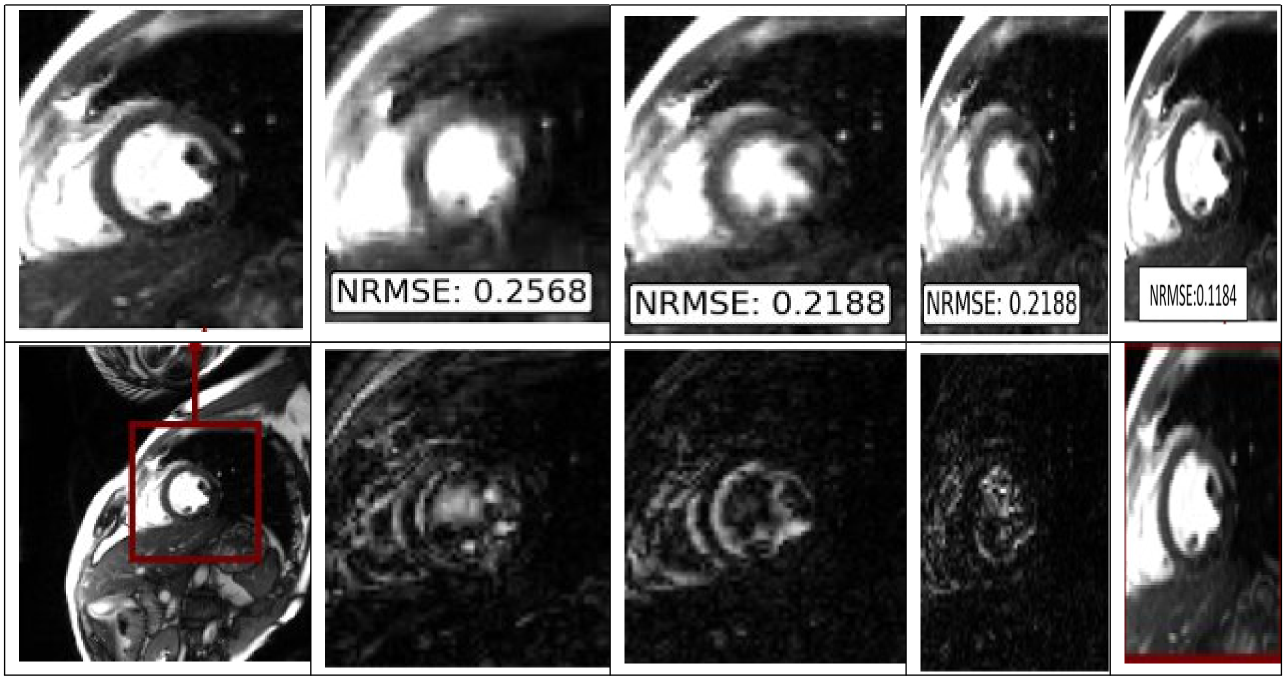
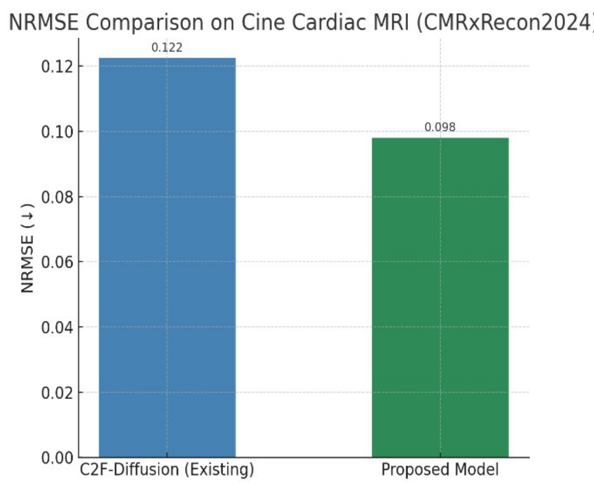


Table 2



Quantitative evaluation on the **CMRxRecon2024 cine cardiac MRI dataset** demonstrates that the proposed model achieves a substantially lower normalized root mean squared error (NRMSE) compared to the existing **C2F-Diffusion** baseline. Specifically, the proposed framework attained an NRMSE of **0.098**, while C2F-Diffusion reported an NRMSE of **0.1225**. Since NRMSE directly measures reconstruction error, with lower values indicating superior performance, these results confirm that the proposed model provides more accurate motion correction and improved temporal alignment across cine frames. The reduction in reconstruction error highlights the benefit of integrating explicit global motion estimation and cardiac-specific priors within the diffusion-based framework, leading to enhanced consistency and fidelity relative to state-of-the-art methods.

Conclusion

This work introduced a deep learning–based framework for **global motion correction in cine cardiac MRI**, explicitly modeling translational, rotational, and contraction/expansion displacements. By integrating dual displacement field estimation, a hierarchical feature encoding–decoding network with frequency-domain channel attention, and a global motion transformation layer, the proposed method achieved improved temporal consistency and reconstruction accuracy compared to state-of-the-art diffusion-based approaches. Evaluation on the CMRxRecon2024 dataset demonstrated a substantial reduction in reconstruction error, confirming the effectiveness of incorporating cardiac-specific global motion priors into cine CMR correction.

Future work will focus on extending this framework beyond in-plane corrections to address more complex motion patterns encountered in dynamic cardiac imaging. Particular emphasis will be placed on developing strategies to handle through-plane displacements and incorporating physiological priors tailored to velocity-encoded MRI sequences.

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