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Q-space-coordinate-guided neural networks for high-fidelity diffusion tensor estimation from minimal diffusion-weighted images

Key words: Diffusion tensor imaging; Diffusion tractography; Deep learning; Fast diffusion tensor estimation; *Q*-space-coordinate information

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Motivation

1. Existing methods largely rely on fixed *q*-space sampling schemes, requiring consistency between training and testing data. Some recent studies have explored sampling-scheme-independent estimation to improve adaptability.

2. Current approaches often neglect the incorporation of *b*-value information, exhibit limited overall flexibility, and fail to maintain high estimation accuracy under non-fixed sampling schemes, making it difficult to balance adaptability and reconstruction quality.

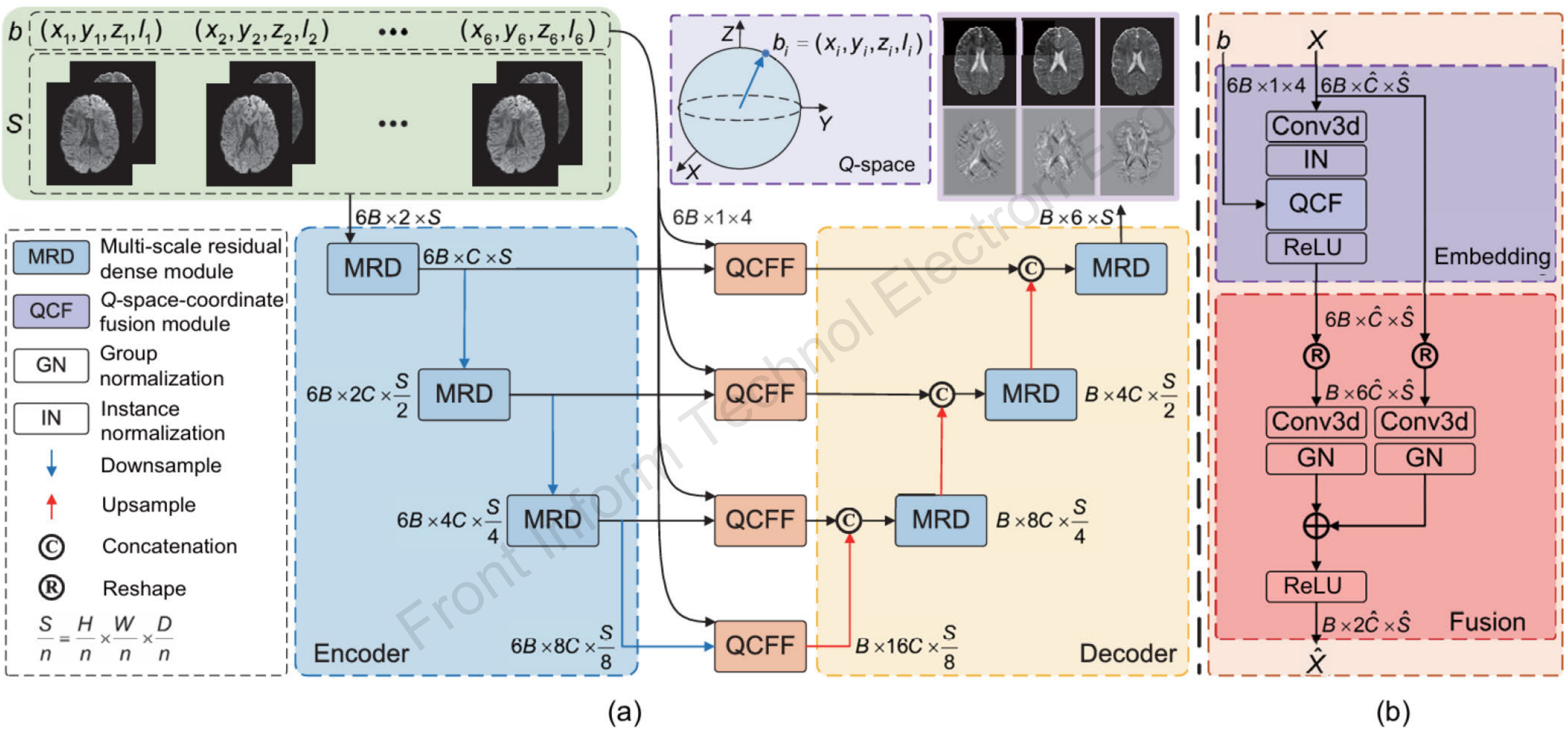
Main idea

1. We propose a flexible and efficient diffusion tensor estimation network, QCG-DTI, which incorporates a *q*-space-embedded feature consistency strategy to ensure the correspondence between *q*-space coordinates and DW images.

2. We introduce a *q*-space coordinate fusion (QCF) module to efficiently embed *q*-space coordinates and a multiscale residual dense (MRD) module to enhance feature extraction and image reconstruction.

3. Experiments on multiple datasets demonstrate that QCG-DTI outperforms state-of-the-art diffusion tensor estimation methods under various *q*-space sampling schemes.

Framework



Architecture of the proposed QCG-DTI: (a) overall framework; (b) enlarged view of the QCF fusion (QCFF) module

Method

1. Directly concatenating all DW images as input may degrade diffusion tensor estimation due to missing correspondence between *q*-space coordinates and DW images.

2. *Q*-space-coordinate-embedded feature consistency strategy integrates input grouping, *q*-space coordinate embedding, and multi-scale feature fusion, enabling the model to capture the correspondence and improve diffusion tensor estimation accuracy.

Algorithm 1 QCG-DTI framework

Input: S_0, S, b, and hyperparameters L_X and L

/* L_X and L are the numbers of input DW images and MRD modules in the shared encoder, respectively. The subscript X denotes the input data, i.e., the set $\{F_{\text{in}}^{(1)}, F_{\text{in}}^{(2)}, \ldots, F_{\text{in}}^{(6)}\}$. */

Output: D_{pred}

for $i = 1, 2, \cdots, L_X$ **do**

$F_{\text{in}}^{i} \leftarrow [S_0, S_i]$

/* Concatenate along the channel dimension. */

$F_{\text{SE},1}^{i} \leftarrow f_{\text{SE},1}\left(F_{\text{in}}^{i}\right)$

$F_{\text{QCF}_1}^{i} \leftarrow f_{\text{QCF}_1}\left(F_{\text{SE},1}^{i}, b_i\right)$

/* Embed the q-space coordinate b_i into the extracted image features. */

for $j = 2, 3, \cdots, L$ **do**

$F_{\text{SE},j}^{i} \leftarrow f_{\text{SE},j}\left(F_{\text{down}}\left(F_{\text{SE},j-1}^{i}\right)\right)$

$F_{\text{QCF}_j}^{i} \leftarrow f_{\text{QCF}_j}\left(F_{\text{SE},j}^{i}, b_i\right)$

end for

$F_{\text{QCF}_{L+1}}^{i} \leftarrow f_{\text{QCF}_{L+1}}\left(F_{\text{down}}\left(F_{\text{SE},L}^{i}\right), b_i\right)$

end for

for $j = 1, 2, \cdots, L+1$ **do**

$F_{\text{QCFF}_j} \leftarrow f_{\text{conv}_j}([F_{\text{QCF}_j}^{1}, F_{\text{QCF}_j}^{2}, F_{\text{QCF}_j}^{3}, F_{\text{QCF}_j}^{4}, F_{\text{QCF}_j}^{5}, F_{\text{QCF}_j}^{6}])$

/* Concatenate and fuse along the channel dimension. */

end for

$f_{\text{Decoder},L} \leftarrow f_{\text{Decoder},L}\left([f_{\text{up}}(F_{\text{QCFF}_{L+1}}), F_{\text{QCFF}_L}]\right)$

/* $f_{\text{up}}(\cdot)$ represents upsampling using resizeconv, and $f_{\text{Decoder},L}(\cdot)$ denotes the MRD operations in the decoder that are symmetric to $f_{\text{SE},L}(\cdot)$. */

for $k = L-1, L-2, \cdots, 1$ **do**

$F_{\text{Decoder},k} \leftarrow f_{\text{Decoder},k}\left([f_{\text{up}}\left(F_{\text{Decoder},k+1}\right), F_{\text{QCFF}_k}]\right)$

end for

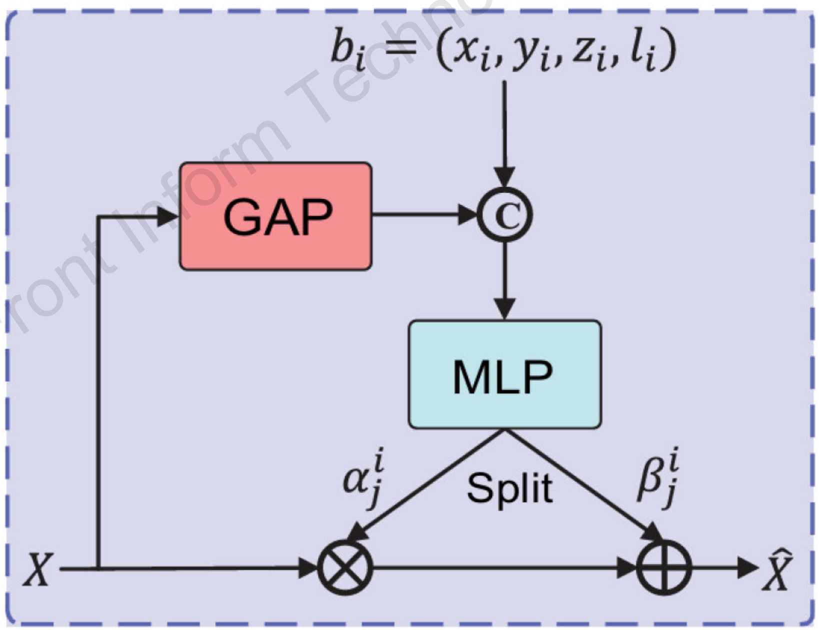
$D_{\text{pred}} \leftarrow f_{\text{conv}}\left(F_{\text{D},1}\right)$

return D_{pred}

Q-space-coordinate-embedded feature consistency strategy

Method

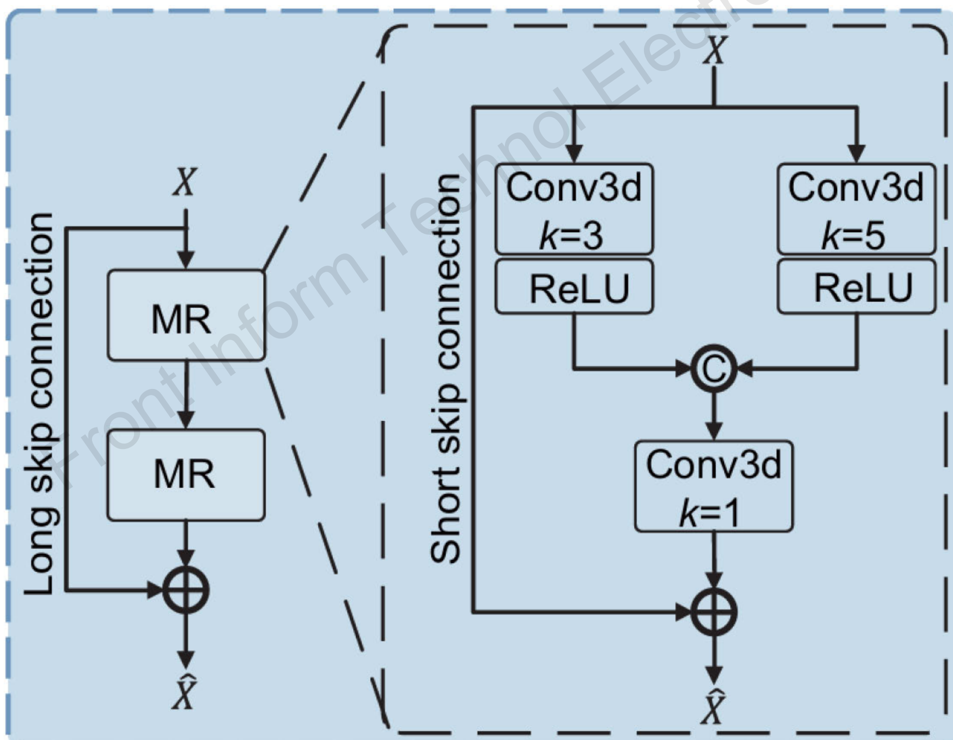
The *q*-space coordinate fusion (QCF) module is designed to efficiently embed *q*-space coordinates into DW image features, addressing the dependence on fixed sampling schemes. Embedding is achieved via a linear transformation along the feature channel dimension of the DW images.



Q-space coordinate fusion module

Method

The multiscale residual dense (MRD) module enhances feature extraction and tensor reconstruction using dual-branch convolutions and skip connections to capture both local and global information from DW images.



Multiscale residual dense module

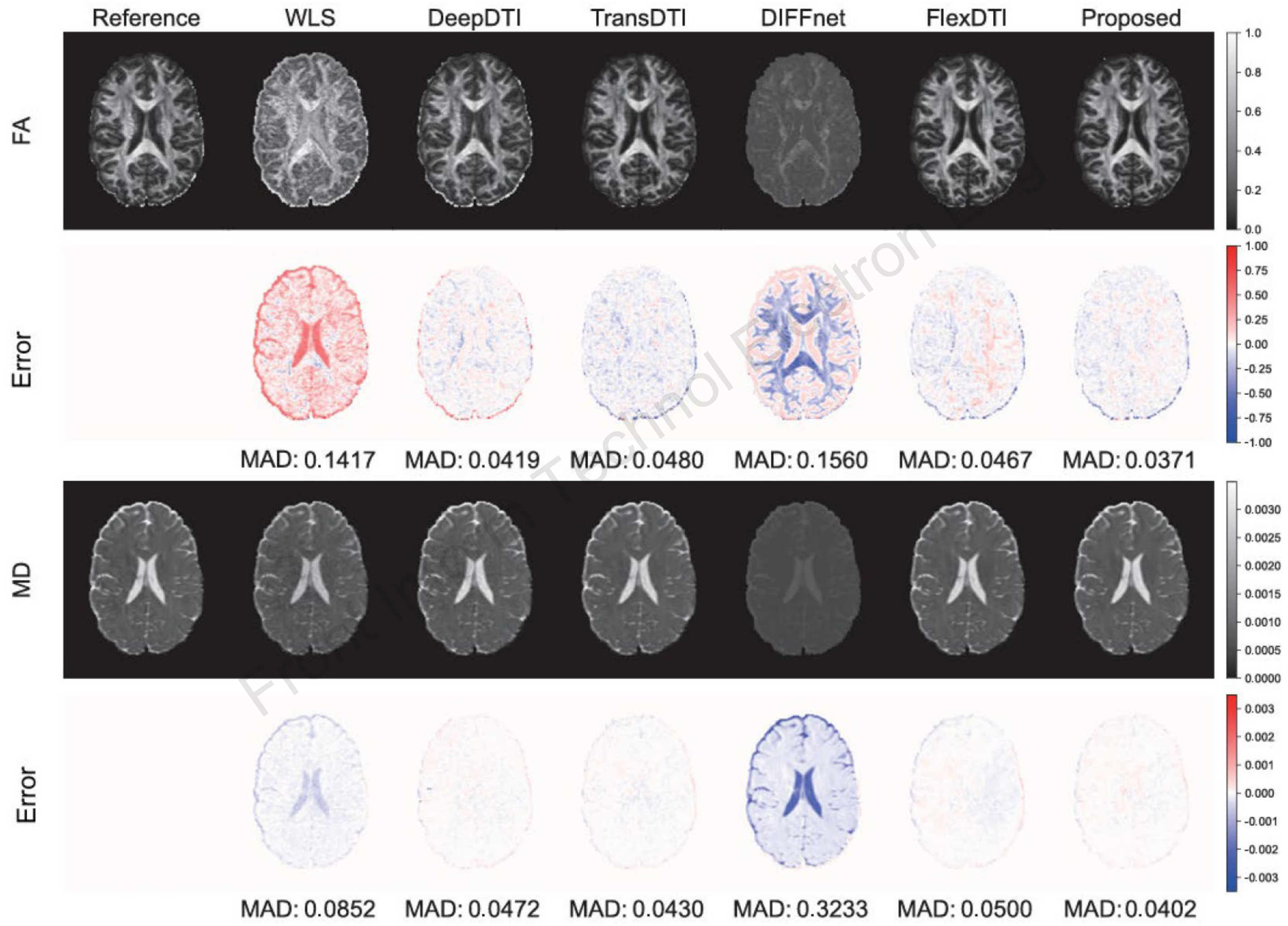
Major results

Comparison of methods on the HCP dataset

Dataset	Method	Tensor	FA	MD	AD	RD	Angle (°)
Fixed	WLS	0.818±0.102	0.1292±0.0361	0.1614±0.0197	0.1501±0.0299	0.1748±0.0346	41.38±1.93
	DeepDTI	0.357±0.038	0.0502±0.0064	0.0592±0.0055	0.0883±0.0121	0.0627±0.0063	29.17±1.67
	TransDTI	0.341±0.024	0.0551±0.0026	0.0553±0.0068	0.0837±0.0060	0.0622±0.0068	29.39±1.05
	DIFFnet	–	0.1364±0.0036	0.4687±0.0234	0.5609±0.0239	0.3738±0.0225	–
	FlexDTI	0.346±0.030	0.0506±0.0024	0.0581±0.0093	0.0837±0.0073	0.0640±0.0089	28.92±1.04
	Proposed	**0.283±0.016**	**0.0453±0.0028**	**0.0473±0.0046**	**0.0688±0.0040**	**0.0524±0.0050**	**25.79±1.00**
Flexible	WLS	0.817±0.102	0.1289±0.0361	0.1614±0.0197	0.1501±0.0299	0.1748±0.0346	41.38±1.93
	DeepDTI	0.850±0.118	0.1492±0.0272	0.1153±0.0364	0.1739±0.0380	0.1467±0.0373	45.37±2.68
	TransDTI	0.768±0.065	0.0767±0.0034	0.0834±0.0170	0.1409±0.0162	0.0871±0.0145	55.77±3.64
	DIFFnet	–	0.1698±0.0459	0.3148±0.0789	0.3445±0.0864	0.2870±0.0754	–
	FlexDTI	0.373±0.041	0.0520±0.0023	0.0663±0.0124	0.0907±0.0112	0.0728±0.0123	29.33±1.11
	Proposed	**0.289±0.019**	**0.0443±0.0027**	**0.0499±0.0060**	**0.0706±0.0045**	**0.0546±0.0062**	**25.67±0.78**

QCG-DTI achieves an average error reduction of 14.40% on datasets with fixed sampling schemes and 20.28% on datasets with flexible sampling schemes.

Major results



Qualitative comparison of different methods on FA and MD

Conclusions

1. We propose QCG-DTI, incorporating a *q*-space-coordinate-embedded feature consistency strategy with QCF and MRD modules, to enable flexible and precise diffusion tensor estimation from DW images.

2. Comprehensive evaluations demonstrate that QCG-DTI outperforms conventional tensor fitting and state-of-the-art deep learning methods, achieving higher accuracy across diverse *q*-space sampling schemes.