Motion Compensation in Diffusion MRI

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Abdominal Diffusion Magnetic Resonance Imaging

∘ Diffusion MRI is a medical imaging technique that uses strong magnetic fields to measure displacements of water molecules inside different organs and internal structures of the body.
∘ Diffusion MRI is a recent tecnique for body applications, although is widespread in clinical practice for tractography and brain diffusion (DTI).
∘ Diffusion weighted imaging (DWI) has multiple applications in oncological studies for several organs, but it is of special relevance in the liver [1].
∘ Echo-Planar Imaging (EPI) has been widely used in abdominal diffusion acquisition either with single or multi-shot radiofrequency pulses.
∘ DWI requires the acquisition of different b-values over the same anatomical region. The signal will suffer an exponential decay proportional to the quantity of diffusion in the excited zone.
∘ Apparent Diffusion Coefficient (ADC) is a well-known diffusion parameter, usually measured with b-values lower than 800 s/mm2, so that the inherent SNR is favorable. However, for more complex models higher b-values are required.

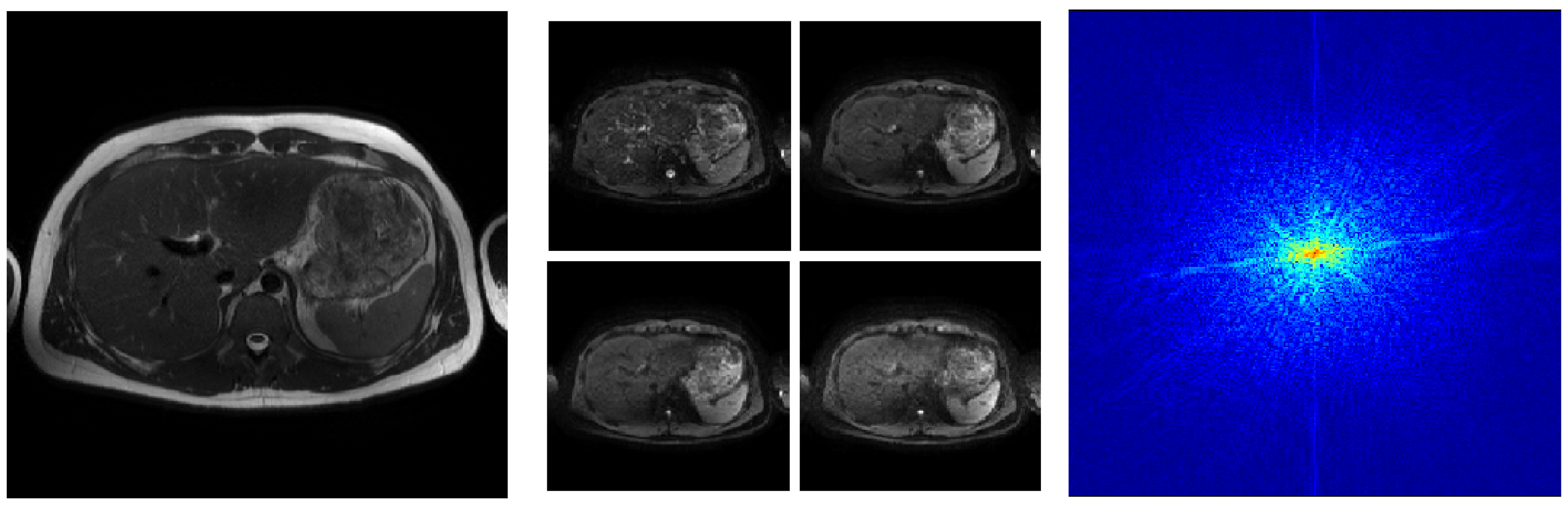

Figure 1: T2 Weighted MRI liver acquisition example (left). Diffusion Weigthed Imaging acquisition examples with different b-values: 0, 200, 400 and 600 s/mm2 (center). Fully sampled k-space image (right).

Compressed Sensing

∘ Compressed Sensing theory (CS) [2, 3] states that, when a signal has a *sparse* representation in a certain domain, it can be recovered from a significantly smaller set of measurements than indicated by the Nyquist theorem.

∘ In dynamic MRI, most of the changes due to the motion of the structures lead to abrupt intensity changes, consequently, reducing the sparsity of the signal in the transformed domain. We can used some knowledge about the motion to restore this sparsity [4].

∘ We can introduce, respectively, the estimated respiratory and cardiac motion information in the CS reconstruction by modifying the reconstruction problem.

∘ Initially, a multi-slice/multi-contrast reconstruction is performed with respiratory binning according to the b-value and respiratory phase.

∘ The image $\mathbf{m}$ can be recovered from a small set of measurements $\mathbf{y}$ by solving the following optimization problem:

$$\underset{\mathbf{m}}{\text{minimize}} \ \frac{1}{2}\sum_{b=1}^{B} \| \mathbf{y_b} - \mathbf{E}\mathbf{m_b} \|_{\ell_2}^2 + \lambda \| \nabla \mathbf{m_b} \|_{\ell_{2,1}}$$

where $\nabla\mathbf{m}$ is the regularization term and $\mathbf{E}$ is the encoding operator that comprises: 2D FT, coil sensitivities and undersampling.

∘ Once reconstructed these images, the respiratory motion estimation is introduced by means of groupwise registration method over every acquired b-value.

∘ Multi-slice and multi-contrast reconstruction with respiratory motion compensation discriminating cardiac phases. Another binning will be performed over the acquired data, exploiting the inherent redundance between b-values and cardiac phases.

$$\underset{\mathbf{m}}{\text{minimize}} \ \frac{1}{2}\sum_{b=1}^{B} \| \mathbf{y_b} - \mathbf{G}\mathbf{m_b} \|_{\ell_2}^2 + \lambda \| \nabla \mathbf{m} \|_{\ell_{2,1}}$$

where $\mathbf{G}$ is the encoding operator that takes into account motion and undersampling effects simultaneously.

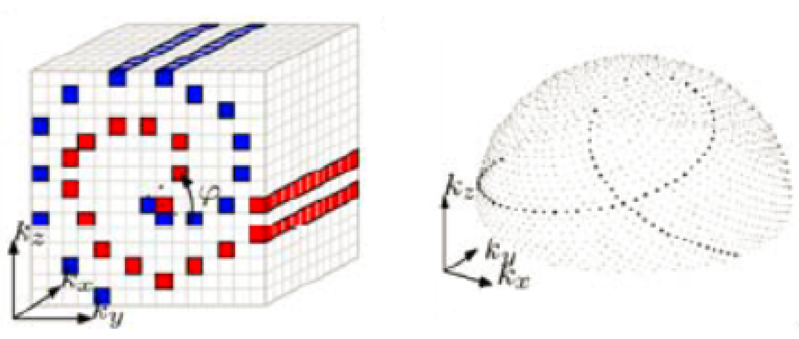

Figure 2: Proposed trajectories for the k-space subsampling for accelerated 3D reconstruction. Corresponding for cilindrical-spiral (left) and radial-spiral (right).

Two-Stage Reconstruction

∘ Reconstruction problem: lack of the true dynamic image to estimate the motion information from, also affected by the motion artifacts and the ones introduced by the undersampling pattern.
∘ The main drawbacks for the acquisition are the motion related artifacts produced by respiratory and cardiac motion:
∘ Local deformations are induced by the heartbeats, which originate a decayment of the diffusion signal, specially in the left lobe of the liver.
∘ Respiratory motion introduces diffusion artifacts and blurring in the anatomical structures. Respiratory triggering is widely in many clinical studies, besides, for the left lobe, cardiac triggering is also advised. However, time scanning is signinficantly increased (up to 6 times) [5].
∘ SMS (simultaneous multislice) is a novel tecnique based on multiband excitation, with such a design, multiple zones can be acquired simultaneously.

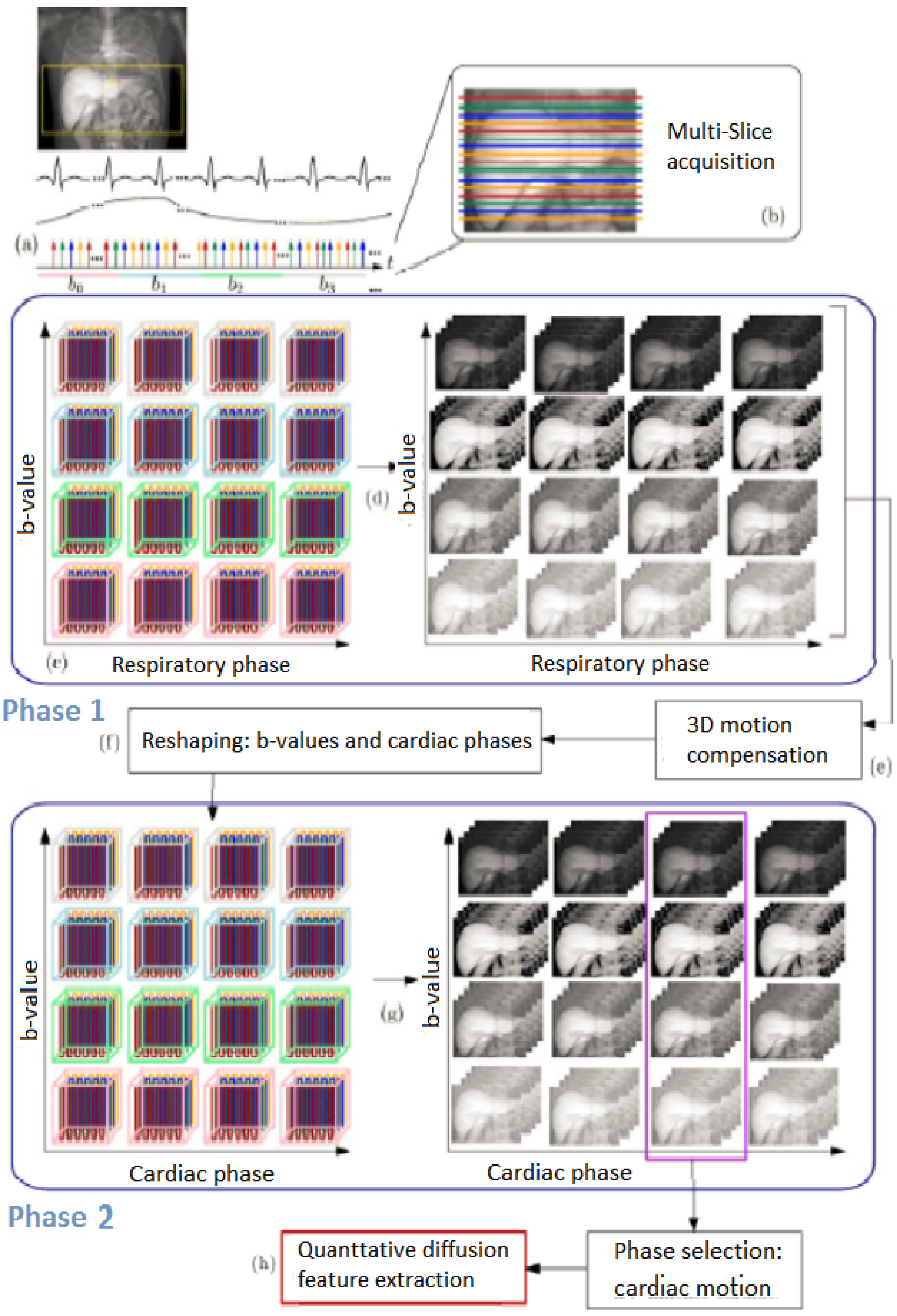

Figure 3: Diagram of the proposal for the multi-parameter reconstruction in abdominal diffusion.

Groupwise Registration

∘ Motion estimation robust against undersampling artifacts and flexible enough to describe both cardiac and respiratory motion.

Method	Description	Comments
Single reference	Each frame is registered to one fixed frame used as a reference.	Need for a high quality reference frame. Frames far from the reference harder to register. Only two frames.
Sequential	Each frame is registered to the previous or following one, used as reference.	Only two frames are available. Forward plus backward registration.
Groupwise	The whole sequence is registered jointly to a common, average motion state.	The whole information available to the registration algorithm. Common reference frame.

∘ Groupwise registration succeeds in finding the optimal parameter set from a common reference framework obtained from the whole image space.

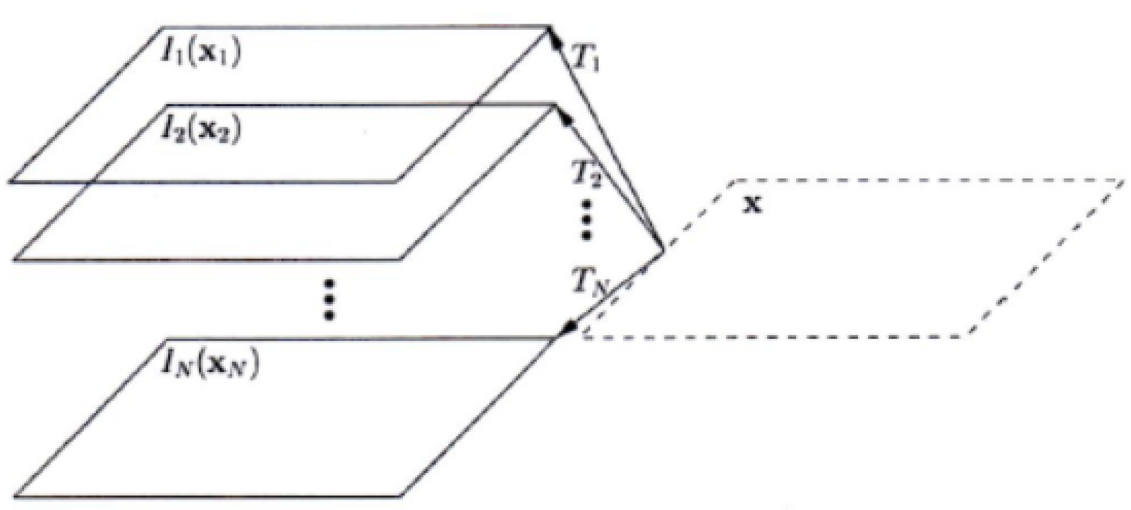

Figure 4: Graphic representation of groupwise registration.

Key components:
∘ **Non rigid deformation model: Free Form Deformations** based on B-splines [6]:

$$\mathbf{T}(x,y) = (x,y) + \sum_{j,k} B_x(u_j(x)) B_y(v_k(y)) \boldsymbol{\theta}_{j,k}$$

∘ **Groupwise registration metric** [7] . Variance of intensities as sum of squared differences:

$$V(\mathbf{x}) = \frac{1}{N}\sum_{n=1}^{N}\left(m_n(T_n(\mathbf{x})) - \frac{1}{N}\sum_{k=1}^{N} m_k(T_k(\mathbf{x}))\right)^2$$

∘ **Spatio-temporal regularization**:

$$C(T_\theta) = \frac{1}{|\chi|N}\sum_{n=1}^{N}\int_{\chi} \lambda_1\left(\left|\frac{\partial T_n(\mathbf{x})}{\partial x}\right|^2 + \left|\frac{\partial T_n(\mathbf{x})}{\partial y}\right|^2\right) + \lambda_2\left(\left|\frac{\partial^2 T_n(\mathbf{x})}{\partial x^2}\right|^2 + \left|\frac{\partial^2 T_n(\mathbf{x})}{\partial y^2}\right|^2 + \beta\left|\frac{\partial^2 T_n(\mathbf{x})}{\partial x \partial y}\right|^2\right) + \lambda_3\left|\frac{\partial T_n(\mathbf{x})}{\partial n}\right|^2 + \lambda_4\left|\frac{\partial^2 T_n(\mathbf{x})}{\partial n^2}\right|^2 d\mathbf{x}$$

∘ XCAT environment produces realistic phantoms for cardio-torso simulation. Besides, motion of different organs can be introduced, obtaining full isotropic synthetic 3D images [8] .

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