Retrospective Motion Correction for Cardiovascular and Body Imaging

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Motion during Cardiovascular and Body MRI

Clinical MRI protocols are the result of a trade-off between spatial and/or temporal resolution, signal-to-noise ratio (SNR), contrast and acquisition duration. The latter is often the limiting factor in MRI of moving organs such as in cardiovascular and body imaging. This is because clinical protocols most often deal with motion through cardiac synchronization (e.g. using the ECG) and patient cooperation (breath-holding). As a result a sequence should not exceed 20-30 sec, which implies decreasing either resolution, SNR or contrast. Acceleration methods such as parallel imaging and compressed sensing can minimize the loss but they still intrinsically lower the SNR, at least by a factor $\sqrt{R}$ with R the acceleration factor. To improve image quality further the only (generally applicable) alternative is therefore to get rid of the breath-hold constraint. This implies developing methods for perfect management of patient motion. Respiratory synchronization (e.g. using navigators) can be used but is difficult due to organs' possible drifting over long periods of time (typically 5 to 15 min) and relatively inefficient due to rejection of large amounts of data.

Motion correction is an alternative solution. Prospective motion correction should be used whenever possible because it better preserves the spin history. However it is limited to affine motion correction. This is because spatial encoding in MRI uses spatially linear gradients, therefore only linear changes of the coordinate system can be achieved by modifying the gradient and radiofrequency (RF) waveforms in real-time. Another limitation of prospective methods is the assumption that the spatial variations in each sensitivity map are much smaller than motion. A general description of motion using “elastic” displacements (also termed non-affine or non-rigid) is more realistic for representing breathing or cardiac-induced motion for instance. But it is also more difficult to deal with because: i) it necessitates dedicated image reconstruction techniques ; ii) the description of motion requires more parameters and these parameters are more difficult to estimate.

Assumptions about Motion

In this course we will focus on reconstruction methods aimed at correcting for general motion (possibly non-rigid) during MRI acquisition.

We will assume that motion between the RF excitation and the sampling of k-space data can be neglected. When this holds, motion can be considered to occur between the successive phase encoding steps and therefore only the spatial encoding process is affected, resulting in ghosting and blurring artifacts (1). Such motion is often termed inter-view (as opposed to intra-view). It should be noted that this assumption is not always valid. For instance fast motion during sequences such as RARE or diffusion-weighted imaging is likely to cause signal dropouts. Such situations should first be handled through efficient synchronization, sequence design optimizations (e.g. gradient moment nulling) and/or prospective correction techniques, which may ultimately be combined with the reconstruction methods described hereafter.

More generally speaking, it will be assumed that a motion-corrected image does exist, which means that there exists a reference motion state from which any motion state can be derived by a spatial deformation of the imaged organs/tissues (and only by a spatial deformation). In terms of physics, this assumption can be thought of as a signal conservation rule (the signal being what is "seen" by the imaging system), analogous to mass conservation. Therefore large through-plane or out-of-volume motion, contrast changes during the course of the sequence or changes of the magnetization due to spin history effects should be treated carefully. This assumption should also be interpreted in terms of physiology. For instance, phase-contrast cardiac MRI during free breathing may use data from different respiratory motion states which correspond to different velocities due to cardiac-respiratory interactions. Therefore those assumptions should always be kept in mind and interpreted.

General Framework for Motion-Compensated Image Reconstruction

Forward Acquisition Model

Under these assumptions MR image reconstruction in the presence of non-rigid inter-view motion has been described and demonstrated in (2,3). Related work and extensions of this framework can be found in (4–12). Mathematically it consists of solving an inverse problem of the form :

$$s = E\,\rho_0. \quad [1]$$

Here ρ_0 denotes the unknown (static) imaged subject at an arbitrary time t_0 (reference motion state of the subject) and is represented by a vector of $N_{xyz} = N_x N_y N_z$ elements, with N_x, N_y and N_z the size of the image in frequency, phase and slice direction respectively. The k-space data vector s is of length $N_{acq} = N_c N_{ex} N_{xyz}$ with N_{ex} the number of excitations (number of acquisitions of each k-space view) and N_c the number of coil receivers. The operator E describes the motion-corrupted MRI acquisition process and is an N_{acq}xN_{xyz} matrix further described by:

$$E = \begin{bmatrix} \xi_1 F\, S_1 T_1 \\ \vdots \\ \xi_M F\, S_1 T_M \\ \hline \vdots \\ \hline \xi_1 F\, S_{N_c} T_1 \\ \vdots \\ \xi_M F\, S_{N_c} T_M \end{bmatrix}. \quad [2]$$

The matrix E is composed of vertical blocks, each of them accounting for one coil receiver $c \in \{1 \ldots N_c\}$ and one motion state $m \in \{1 \ldots M\}$; T_m is an image warping operator that deforms the image from its reference motion state to the m^{th} motion state ; S_c is the sensitivity weighting operator of the c^{th}coil (diagonal operator with sensitivity values on the diagonal) ; F is the Fourier transformation operator ; ξ_m is the sampling operator that selects k-space data that are acquired while the subject is in the m^{th} motion state (in case of non-Cartesian sampling, ξ_m would be an interpolation operator). Except F, all matrices composing E are sparse. Specifically, each T_m matrix is an interpolation operator. For instance, using a linear interpolation kernel with 3D images means that T_m is computing the intensity value of each voxel of the deformed image as a linear combination of $2^3 = 8$ voxels from the reference image, yielding 8 non-zero elements per row in T_m.

In the simplest implementation the m motion states simply describe the subject's motion states at physical times corresponding to the k-space view ordering. In a more efficient implementation k-space views corresponding to similar motion states (e.g. as assessed by external sensors or navigators) are grouped and considered to be part of the same motion state (4).

Solving the Linear System

Equations 1 and 2 define a large-scale linear algebraic system of equations. It is generally solved using a matrix-free solver (i.e. a solver which does not require the E matrix to be stored explicitly) such as the conjugate gradient, GMRES (generalized minimal residual) or LSQR (least squares). Some of these solvers only operate on square matrices, in which case it is necessary to form the equivalent system:

$$E^H E\,\rho_0 = E^H s, \quad [3]$$

where E^H is the Hermitian transpose of E. By construction, $E^H E$ is square and Hermitian symmetric. Moreover if it has full rank, $E^H E$ is positive-definite which guarantees convergence for the conjugate gradient. It is important to use the actual mathematical transpose E^H rather than an approximate, especially for the T_m sparse matrices (for non-rigid motion this is not the same as estimating the inverse transformation) because left-multiplying by a matrix other than E^H may worsen the condition number of the system.

In practice the system is ill-conditioned. One reason for that is possible errors in the motion operators (and sensitivity maps). Another reason is the possible loss of information due to rotational motion: an extreme example would be a two-shot acquisition, with a 90° rotation of the object between the two shots ; this would cause large areas of k-space to be left unsampled.

Methods for improving the conditioning of the system include (3): i) using $N_{ex} > 1$ (typically $N_{ex} = 3\ to\ 4$) so that each k-space data is acquired at different (random) motion states, thus adding new linearly independent data to the system ; ii) using additional constraints such as Tikhonov regularization (i.e. inverting $E^H E + \lambda\, Id$ instead of $E^H E$). This framework has also been used in combination with compressed sensing (10) which may also help solving ill-conditioned systems by promoting sparse solutions.

Correlated noise between receiver channels can be handled before the reconstruction by creating a virtual, perfectly decorrelated set of channels (7,13). This can be done by forming appropriate linear combinations (derived from the noise covariance matrix) of the k-spaces and sensitivity maps. Therefore it is not necessary to add noise covariance matrices in the equations.

Note: Assumptions about B_0 and B_1 Fields

In this framework it is assumed that the B_0 and B_1 fields are not affected by motion. Regarding the reception B_1 fields (i.e. the sensitivity maps), this means that the motion of the coil receiver itself and coil loading changes are neglected. However changes in sensitivity "seen" by moving voxels are taken into account due to the motion operators T_m being applied before sensitivity weighting in the acquisition model (3).

For some applications the assumption of static B_0 and B_1 fields may not be true. One example is MR thermometry based on the proton resonance frequency shift which has been reported to be sensitive to breathing-induced phase changes (14,15). Calibration methods have been proposed for measuring time-varying field maps that can be used for correcting such phase changes using lookup tables or model-based methods (16). The framework described here might be extended by adding varying B_0 and/or B_1 maps corresponding to each motion state in the model.

Motion-Compensated Averaging

A particular situation occurs when real-time imaging is used in combination with a large number of excitations ($N_{ex} \gg 1$). Here motion during the sampling of a single (generally undersampled) k-space may be neglected. A series of images can be reconstructed with parallel imaging or fast dynamic imaging techniques without motion artifacts but with low SNR. Non-rigid image registration is then used to align all frames. After registration, averaging is performed to increase SNR without introducing significant motion artifacts (unlike conventional averaging). This strategy has been demonstrated in (17–19). It has also been combined with the aforementioned matrix framework in order to reduce residual motion artifacts further (12,20).

Motion-Compensated Dynamic MRI

Another interesting scenario is dynamic imaging. Some applications, like cardiac cine imaging, aim at imaging motion. It has been proposed to model and search for motion between frames (21) rather than searching for changes in pixel intensities as it is usually done in k-t methods. Other applications, like first pass perfusion imaging, aim at imaging a contrast uptake and consider motion as an artifact. In such cases it is possible to extend the acquisition model in Eq. [1] with a signal model (e.g. a B-spline model) describing contrast uptake (8).

Compressed-sensing based dynamic MRI, namely with the k-t FOCUSS method, has also been extended with a motion estimation and compensation scheme (22). The idea is to estimate and compensate frame-to-frame motion using image registration techniques so that only the residual image needs to be encoded (the difference between the registered images becomes sparser). This approach motion has been shown to help encoding the dynamic scene more efficiently. Another application of this idea has been demonstrated in (10) using an extended version of the motion-compensated reconstruction framework accounting for dynamic compressed sensing acquisition.

Estimating Motion

The main difficulty in motion-compensated reconstruction is to obtain accurate estimates of the transformation matrices T_m. Various approaches have been described, depending on the pulse sequence used, the type of motion and the desired application.

Image Registration

In motion-compensated averaging, non-rigid image registration techniques have been used in order to estimate displacement fields directly from real-time image series (23,24). With certain sampling schemes such as PROPELLER (25) or golden angle ratio radial sampling (26), low resolution images can be extracted corresponding to each shot in the acquisition; motion can be extracted from such data in k-space domain using Fourier properties of affine transformation (in case of affine motion) or by registration of the low resolution data in image domain (27). Image navigators (i.e. 2D navigators) have also been used (7) in combination with non-rigid registration (28).

Direct Motion Estimation from Tracking Devices or Navigators

If rigid motion is assumed, many techniques have be used for deriving motion parameters, e.g. using external tracking devices (29), image navigators (30), orbital navigators (31) or so-called butterfly navigators (32). Some of them have been used for guiding motion-compensated reconstruction algorithms. So far these have been used mainly in head applications but they might be useful for other organs as well. When using coil arrays with a large number of receivers, analyzing motion independently from each receiver channel provides rigid motion parameters corresponding to localized portions of the field-of-view (32).

Motion Models

In order to ease the estimation of (possibly non-rigid) motion, motion models have been proposed. The idea is to use the pseudo-periodicity of certain types of motion by mapping the motion parameters (either affine parameters or local pixelwise translations) to certain motion monitoring signals. This approach has proved particularly useful in MRI and many other modalities for modeling, correcting or predicting motion (33), especially for respiratory motion. It has been used in particular for MR prospective motion correction (34,35). Respiratory and cardiac motion models have also been constructed from external sensors (9,36) including respiratory belts and/or ECG derived signals, or multiple-coil self-navigating techniques (6,32).

Searching for Motion Parameters that minimize a Cost Function

Motion parameters can also be estimated directly from the motion-corrupted k-space data.

If motion parameters are applied to a given k-space view/shot (e.g. by a phase ramp for a translation), this will affect the resulting image. A metric can be defined for quantifying image quality (often based on image entropy, image-gradient entropy or image gradient norm) and searching for the motion parameters, for each k-space view/shot, that minimize this metric (37). This approach is often termed autofocussing in the literature (37–43,32). Generally, authors have applied the motion correction directly in k-space domain, thus not explicitly solving for the linear system in Eq. [1]. The resulting motion-corrected image is therefore the result of an empirical inversion of Eq. [1] (rather than using the mathematical inverse) which may not yield an optimal solution as explained in (2). Autofocussing with additional constraints about motion has been proposed so that the solution follows a known motion path in the time dimension (e.g. known from navigators), which allows pixelwise translations (i.e. non-rigid motion) to be optimized (32).

The norm of the residual reconstruction error has also been used as a metric (4). The gradient of this cost function is easily expressed as a function of the estimated image gradient and the non-rigid displacement error (using the optic flow equation). The choice of this metric allows both the image and the motion to be optimized jointly from the corrupted k-space data using an alternating optimization procedure. Such a reconstruction strategy is termed GRICS in the literature (4,6,8,9,11). In GRICS external sensors and/or navigator data can be used as driving signals for a motion model that allows non-rigid displacements.

Similar approaches to GRICS have been described in PET reconstruction (44,45) for jointly reconstructing the image and the motion. In principle this strategy can be applied to all imaging modalities (46). Such problems can be formalized as solving the following joint optimization problem:

$$\min_{(\rho_0,\alpha)} \|E(\alpha)\rho_0 - s\|^2 + \mu\, R(\alpha), \qquad [4]$$

with $\rho_0$the motion-corrected image and α of vector of parameters used to form the $T_m(\alpha)$ matrices (i.e. α are the degrees of freedom for the motion model) . $R(\alpha)$ is a regularizer that constrains the motion model to be spatially smooth, e.g. $R(\alpha) = \|\nabla\alpha\|^2$ (4). More advanced regularizers have been proposed including non-quadratic regularizers (46) and implicit regularization where R is omitted and α described only in vertices of an adaptive mesh (11). Problem [4] can be solved by alternating optimization and necessitates a multi-resolution implementation in order to estimate large displacements.

Outlook

In general image quality in cardiovascular and body MRI protocols is lower than that obtained in neurological or musculoskeletal MRI, especially in terms of spatial resolution. The constraints imposed by physiological motion are among the main reasons for that. Retrospective motion correction methods have therefore the potential for reducing this gap. Advanced methods have been described for detecting and correcting complex motion like those occurring in cardiovascular and body MRI. Rigorous mathematical methods can be used for both image reconstruction and motion estimation. Some of these methods are still computationally expensive, however advances in parallel computing architectures is likely to make them more widely available in the future. Meanwhile advances in navigator design and processing or novel equipments such as MR-compatible ultrasound probes (47) might help to construct more and more accurate motion models. One of the main challenges in the future may be the estimation of highly irregular or unpredictable motion such as cardiac arrhythmia or peristalsis.

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