MRI IMAGE RECONSTRUCTION USING MULTIFRAME INTEGRATION

Krzysztof Malczewski, Ryszard Stasinski

Department of Electronics and Telecommunications,
Poznan University of Technology, Polanka 3, PL-60-965 Poznan, Poland
email: kmal@et.put.poznan.pl, rstasins@et.put.poznan.pl

ABSTRACT

The MRI reconstruction based on super-resolution back-projection algorithm is presented in the paper. It is shown that the approach improves MRI spatial resolution in cases when PROPELLER sequences are used. The PROPELLER MRI method collects data in rectangular strips rotated around the origin of the k-space. Inter-strip patient motion is the premise for the use of super-resolution technique. Images obtained from sets of irregularly located frequency domain samples are combined into the high resolution MRI image. The super-resolution reconstruction replaces usually applied direct averaging of low-resolution images.

Index Terms— MRI, PROPELLER, super-resolution

1. INTRODUCTION

Magnetic resonance imaging (MRI) is well known as a non-invasive method routinely used to produce high-quality images of the body's internal tissues. One of its most promising techniques currently available is PROPELLER (Periodically Rotated Overlapping Parallel Lines with Enhanced Reconstruction) MRI. Motion of a subject during the MRI acquisition generates artifacts and blurring in the resulting image. The PROPELLER technique usually reduces motion artifacts in MRI. Algorithms applied by PROPELLER MRI to estimate and compensate for rigid-body patient motion has been extensively analyzed [1].

Super-resolution (SR) is a group of methods aimed at obtaining high resolution images from sets of low-resolution ones. The motion between low-resolution images is the key premise here. In the case of MRI if the imaging volume is acquired two or more times with small spatial shifts between acquisitions, combination of the data sets using an iterative super-resolution algorithm gives improved resolution and better edge definition in the slice-select direction than simple low-resolution images averaging. For the first time some SR techniques have been applied to MRI in [2]. R. Peeters proposed MRI super-resolution algorithm to reduce slice thickness in functional MRI [4]. H. Greenspan, G. Oz, N. Kiryati and S. Peled proposed MRI reconstruction using super-resolution [3] which improved spatial resolution in cases when spatially-selective RF pulses are used for localization. In this paper the back-propagation SR image reconstruction method is used for improving PROPELLER MRI. Low-resolution images are obtained from frequency-domain strips by the conjugate gradient method with non-uniform FFT (NUFFT) at its core. It is shown that, indeed, the new technique enhances the PROPELLER MRI images.

2. PROPELLER DATA ACQUISITION

Data acquisition procedure for DTT MR (diffusion tensor tomography MRI) imaging is based on the PROPELLER method proposed in [5]. Here, the resulting k-space trajectories are called strips, as frequency-domain image is acquired along collections of straight lines forming rectangular patterns ("strips"), see Fig.1. K-space is filled out by rotating those strips around the center of the k-space. The key idea of PROPELLER is that the circular region at the center of the k-space is covered by many strips. Due to data redundancy, effective information correction can be performed to reduce patient motion artifacts and to improve the SNR. The PROPELLER technique offers an opportunity to choose the diffusion gradient direction while acquiring each k-strip. The conventional procedure is to acquire full set of PROPELLER data with a fixed direction of the diffusion gradient and to reconstruct the corresponding component of the tensor.

3. MRI IMAGE RECONSTRUCTION PROCEDURES

Recently, sampling of the MR signals on a rectangular regularly sampled grid in k-space has been the most popular acquisition method. This regularity was motivated by the use of an easy image reconstruction technique based on the Fast Fourier Transform. Presently, non-uniform sampling patterns of the k-space, such as radial, spiral, or PROPELLER, are gaining importance in various MRI applications. The image reconstruction techniques for arbitrary irregularly sampled grids may be divided into two groups. The first one, called regridding, consists of computationally inexpensive resampling and interpolation of a kernel function into a regularly sampled grid. The next group employs numerical-optimization methods that minimize a least-squares cost function. Optimization procedures may handle nonuniform coil sensitivity and off-resonance effects, improve noise suppression, and provide a robust solution within a larger parametric domain [4]. These methods have proved their effectiveness in many clinical applications and imaging methods, while non-uniform acquisition schemes show their capability to suppress noise and to reduce artifacts caused by motion and by eddy currents in functional [6], cardiac [7], arterial [8], and spine [9] imaging as well as others.

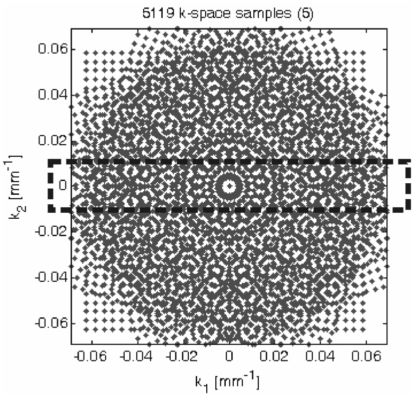

Fig. 1. PROPELLER strips, dash lines show a single data strip.

In the iterative method of reconstructing field-corrected MR images presented in the paper we use a min–max criterion to derive the temporal interpolator [10]. This interpolator provides fast, accurate, field-corrected image reconstruction even when the field map is not smooth. There are two major steps in most methods for field-corrected MR image reconstruction. Firstly, it is necessary to obtain an estimate of the field map that deals with the spatial distribution of magnetic field inhomogeneities. In this paper field-corrected MR image reconstruction is using that field map to form a reconstructed image of the transverse magnetization. An accurate, spatially undistorted field map is assumed to be available. When the field map is obtained, one of methods of field-corrected image reconstruction, the conjugate phase method [11] tries to compensate for the phase accrual due to the off-resonance at each time point. Sutton [11] focused on field inhomogeneities, one can also apply iterative image reconstruction methods to compensate for other physical phenomena such as deviations in k-space trajectory and relaxation effects [10]. The degradation model applied in the paper does not require any assumption about its nature, and is therefore applicable to intersecting k-space trajectories such as PROPELLER's strips. The major disadvantage of iterative reconstruction methods has been their computational complexity. Fessler et all [12] developed accurate and fast non-uniform fast Fourier transform (NUFFT), then the method has been applied to MRI data with spiral k-space trajectories. Namely, the MR image reconstruction problem is closely related to the problem of reconstructing a band-limited signal from nonuniform set of samples in the frequency domain space. Strohmer suggested the use of complex exponentials for finite-dimensional approximations in such problems, and proposed to use an iterative CG reconstruction method with the NUFFT approach at its core [13]. In the algorithm presented below NUFFT-"reverse gridding" and conjugate gradient iterative scheme were combined. It should be noted, that standard NUFFT method by itself does not allow for the compensation of field inhomogeneity effects because the integral signal equation for MR is not a Fourier transform when field inhomogeneities are included. Sutton [10] inspired by the time-segmented conjugate-phase reconstruction approach proposed a fast time-segmented forward projector, and its adjoint, that accounts for field effects and uses the NUFFT. We applied this concept in PROPELLER strip images reconstruction scheme.

4. MRI PROPELLER IMAGE RECONSTRUCTION FROM A SINGLE STRIP

In MRI, ignoring relaxation effects, the *z*-th strip signal equation is given by [11]:

$$s_z(t) = \int \tilde{f}(r)c(r)e^{-i\omega(r)(t+T_E)}e^{-i2\pi(k(t)\cdot r)}dr \qquad (1)$$

where $s_z(t)$ is the complex baseband signal at time t during the z-th strip readout, T_E is the echo time, $\tilde{f}(r)$ is a continuous function of the object's transverse magnetization at location r immediately following the spin preparation step, $c(r)$ is the sensitivity map of the receiver coil, $\omega(r)$ is the field inhomogeneity present at r, and *k(t)* is the k-space trajectory. For simplicity we let $f(r) = \tilde{f}(r)c(r)e^{-i\omega(r)T_E}$. After discretization *z*-th strip signal equation is as follows:

$$s_z(t) \approx \Phi(k(t))\sum_{n=0}^{N-1} f_n e^{-i\omega_n t}e^{-i2\pi(k(t)\cdot r_n)} \qquad (2)$$

where $\Phi(k(t))$ denotes Fourier Transform of $\phi(r)$, the voxel indicator function [11]. In PROPELLER MRI strip measurements are noisy samples of the signal (1):

$$y_i = s(t_i) + \varepsilon_i,\ i = 1,\dots,M\ ,$$

where ε_i denotes noise. Assuming that the dominant noise is the white Gaussian one, we estimate y_i by minimizing the following penalized least-squares cost function

$$\psi(f) = \frac{1}{2}\|y - Af\|^2 + \beta R(f) \text{ so that,}$$

$$\hat{f} = \arg\min_f \psi(f).$$

Computation of Af corresponds to evaluation of (2). The $R(f)$ is a regularization function, that penalizes the roughness of the estimated image. This regularization can decrease the condition number of the image reconstruction problem and, therefore, speed up the convergence. Minimization of cost function is realized iteratively by the conjugate gradient algorithm [11].

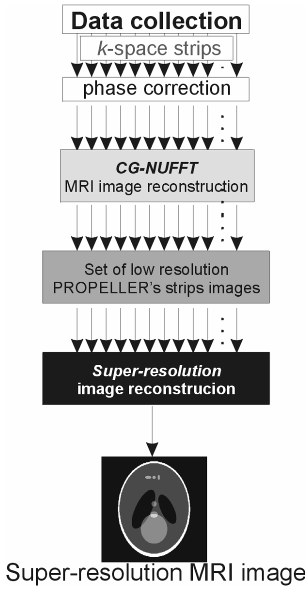

Fig. 2. Scheme for the proposed super resolution image reconstruction from k-space samples

As in PROPELLER k-space trajectories are not Cartesian grids, multiplication by the matrix A is the most computationally demanding operation of the conjugate gradient algorithm. Nevertheless, a Non-Uniform Fast Fourier Transform (NUFFT) can be used for this purpose to rapidly and accurately evaluate the discrete signal (2). However, the NUFFT method is not directly applicable when the field inhomogeneity is included because (1) is then not a Fourier transform integral.

5. SUPER RESOLUTION MRI IMAGE RECONSTRUCTION

Back-propagation SR technique starts with an initial guess of high-resolution image f^0 [4]. Then the imaging process is simulated to obtain a set of low resolution images $\{g_k^{(0)}\}$ corresponding to the observed input images $\{g_k\}$. If f^0 were the correct high resolution image, then the simulated images $\{g_k^{(0)}\}$ should be identical to the observed images. The difference images $(g_k - g_k^{(n)})$ are used to improve the initial guess by "back projecting" each value in the difference images onto its coresponding field in f^0, yielding an improved high resolution image f^1. This process is repeated iteratively to minimize the residual error. This iterative update scheme can be expressed by:

$$f^{(n+1)} = f^{(n)} + \frac{1}{K}\sum_{k=1}^{K} T_k^{-1}(((g_k - g_k^{(n)}) \uparrow s) * p)$$

where K is the number of low resolution images $\uparrow$ arrow an upsampling operator by a factor s and p is a back projection kernel determined by h and T_k. Taking the average of all discrepancies has the effect of reducing noise.

5.1. Initial guess image estimation

The initial guess image is usually obtained by averaging low resolution images or up-interpolating the reference one. Unfortunately, those approaches may result in convergence and final result accuracy deterioration. This observation prompted us to consider higher complexity initial guess computing procedure. In this paper we propose introductory, partial affine motion compensation followed by iterative image reconstruction from irregularly sampled grid [14]. Image sequence is first processed and only non-rigid motion parameters are compensated. Further parameters are used to compose appropriately positioned irregular set of samples.

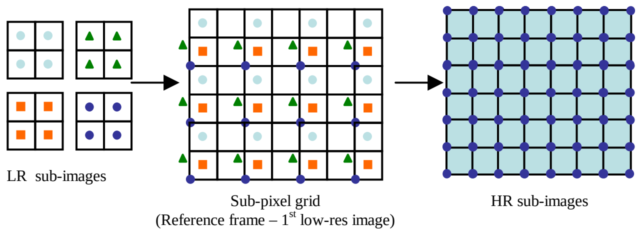

Fig. 3. Irregular – regular sampled grid metamorphosis.

This requires some reconstruction procedure which results in regularly sampled grid. We have employed the projection onto convex sets (POCS) approach supported by biharmonic spline interpolation with Green functions at its core. The POCS algorithm can be expressed as follows:

$$g^{k+1} = \mathrm{B}Rg^k = \mathrm{B}\left[g^k + S_\psi\left(g - g^k\right)\right],$$

where g^k is the reconstructed image after k iterations and S_ψ is a sampling operator that extracts values (luminance) on the irregular grid ψ. R (sample replacement operator) and B (ideal low pass filtering) are projections.
In practice, if a suitable discretization must be applied, last equation is implemented as follows:

$$g_\Lambda^{k+1} = \mathrm{B}\left[g_\Lambda^k + \chi\vartheta_{\psi/\Lambda}\left(g_\Lambda - \vartheta_{\psi/\Lambda}\left(g_\Lambda^k\right)\right)\right].$$

Low pass filtering B is realized over a lattice Λ and χ is a convergence and stability parameter. The $\vartheta_{\psi/\Lambda}$ is an interpolation operator, here it denotes biharmonic spline scheme.
The derivation of the technique in two or more dimensions is similar to the derivation in one dimension. In two dimensions the Green function is equal to

$$\phi_2(x) = |x|^2 (\ln|x| - 1)$$

6. EXPERIMENT

A high-SNR, high-resolution MRI image was shifted and rotated according to affine motion parameters. Natural head motion has been simulated. In this way 12 variations of the original image have been obtained. Gaussian random noise was added to the low resolution images. For each image discrete time Fourier transforms has been calculated.

Twenty shifted images were acquired in order to reconstruct a superresolution image with doubled resolution. It is clearly visible that there are much more details in the obtained in this way high-resolution image, see Fig. 4.

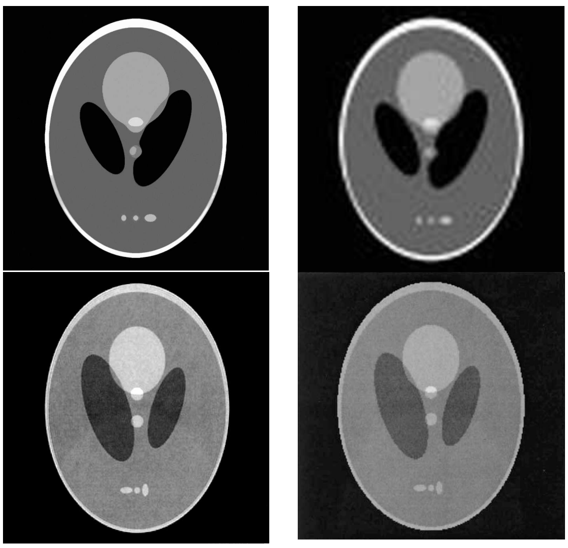

Figure 4. First row: the predicted image from computer-generated data obtained for Shepp-Logan phantom. The interpolated image obtained by applying bilinear interpolation directly to low resolution MRI image. Second row: the super reconstructed MRI-PROPELLER image, the image obtained by “typical” PROPELLER-MRI procedure.

7. CONCLUSION

The new PROPELLER MRI super resolution algorithm based on the back-propagation approach has been presented. In general, when applying super resolution to MRI we can break limits on inherent resolution of existing MR imaging hardware. The same can be told about the proposed algorithm, while it does not add significant time to data reconstruction, if compared to the typical PROPELLER procedure. When using the new algorithm the overall spatial accuracy and stability in the field of view of MRI machines are increased. The algorithm may be easily implemented, as it is based on well known conjugate gradient NUFFT MRI image reconstruction algorithm and on existing motion in MRI data strips. Thus the proposed technique may found applications in all PROPELLER MRI machines.

8. REFERENCES

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