PreLearn: a Learning Method for MRI Parallel Reconstruction

A. Ribés[1], F. Lethimonnier[1], C. Poupon[1]

[1]Service Hospitalier Frédéric Joliot, Commissariat à l'Energie Atomique, Orsay, France

Introduction

We propose a new method for image reconstruction in Parallel MRI: PreLearn (Parallel REconstruction LEARNing). It is applicable to MRI systems where multiple coil receivers having different sensitivities are used. At acquisition stage, coil k-spaces are subsampled in order to accelerate image acquisition. Several reconstruction methods already exist as [1], [2] or [3]. As a consequence of the subsampling, obtained individual coil images are folded. The presented method performs the reconstruction in the image domain; consequently, this reconstruction becomes an unfolding process. The unfolding matrix is calculated by a linear 'learning-by-example' strategy. Sensitivity maps of the coils are not needed as in the classical SENSE (Sensitivity Encoding) technique, [2]. Actually, even if both reconstruction techniques rely on the image domain, PreLearn is based on a different mathematical framework.

Description of the method

In the core of a reconstructing system, a vector **r** containing n_r reconstructed image intensities is generated from another vector **f** containing n_f folded pixels; this is performed by means of an n_r x n_f unfolding matrix, U. We note that n_r is the number of pixels superimposed (or reduction factor) and n_f is the number of coils used in the acquisition system. Mathematically the relationship is expressed as:

$$\mathbf{r} = \mathrm{U}\,\mathbf{f}. \quad (1)$$

The basic idea of PreLearn is to extend relationship (1) by using the concept of neighbourhood. In fact, since sensitivities of the coils are defined by a smooth spatial law, the unfolding matrix U should also be locally smooth from one pixel to another. Taking into account the nearest neighbours, we can consider U to be the same matrix for all of them. This assumption leads to a system of n_n equations as the one in (1), n_n being the number of neighbours plus one (the pixel itself). If we consider a pixel neighbourhood in a 2D MRI slice then n_n=9. Now, we can express the whole system of equations in a unique algebraic expression:

$$\mathrm{R} = \mathrm{U}\,\mathrm{F}, \quad (2)$$

where R is an n_r x n_n matrix of Reference intensities and F is an n_f x n_n matrix containing corresponding Folded pixels. We note that R can be built from a reference image at full resolution and F from the folded images of the coils. Because both matrices have corresponding occurrences on their columns, they form a 'learning-by-example' system. Matrix U can be calculated as $\mathrm{U} = \mathrm{R}\,\mathrm{F}^{-1}$ in case of a squared F. This is generally not true, but in any case matrix U can be estimated using a pseudo-inverse as:

$$\mathrm{U} = \mathrm{R}\,(\mathrm{F}^{H}\mathrm{F})^{-1}\,\mathrm{F}^{H}. \quad (3)$$

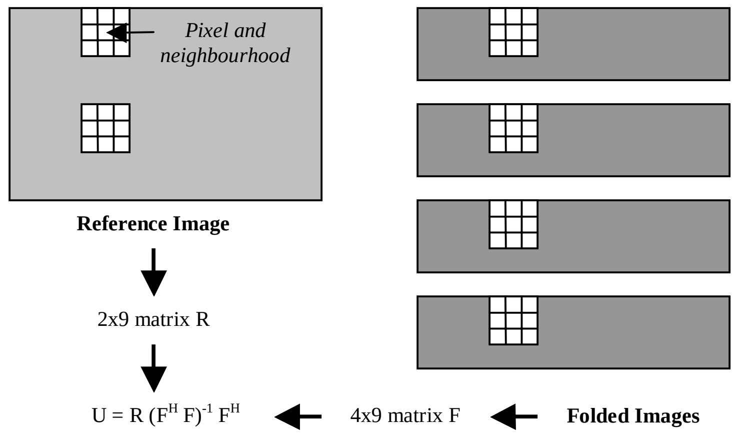

Figure 1. Construction of the Unfolding matrix when using 4 coils and a reduction factor 2.

Figure 1 shows a graphical representation of the construction of U in the particular case of 4 coils and reduction factor 2. An interesting feature of PreLearn can be seen in this example: matrix F contains 4x9=36 elements and matrix R contains 2x9=18 while in a classical SENSE reconstruction the matrix to inverse would contain 4x2=8 elements; PreLearn is potentially more powerful as more information is involved in the system. As a consequence of the method, an image of the patient at the same resolution as desired for the reconstructed images has to be acquired in a calibration step, which is used to build matrices R. The reference image can be acquired with a body coil, if not present a *sum-of-squares* image can be used. The calibration step is identical to the SENSE method but using higher resolution images.

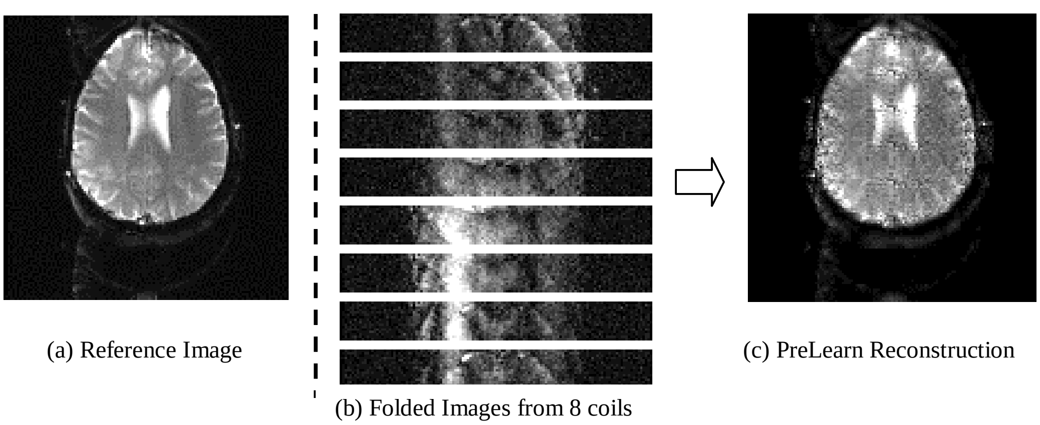

Figure 2. (a) Full resolution sum-of-squares reference image used to build the unfolding matrix in PreLearn, (b) EPI folded images at reduction factor 8 using 8 coils, (c) PreLearn reconstruction.

Results

As an example, we applied this method to a functional MRI (fMRI) series obtained with a 1.5T General Electric Signa system, an 8-channels head coil was used in our test. The acquisition sequence was EPI. We used a 128x128 sum-of-squares image as reference (see Figure 2.a) and eight 128x16 folded images to build the per pixel unfolding operator. These training images were the result of averaging all images of the fMRI series to decrease the effect of noise. In Figure 2 we show the reconstruction of the last sample of the fMRI series: (b) the 8 folded images using reduction factor 8 and (c) its reconstruction using PreLearn.

Conclusion: A new method for Parallel MRI reconstruction has been proposed. The first tests were performed on the reconstruction of fMRI series. Images of acceptable visual quality are obtained at reduction factor 8 using 8 antennas at 1.5T. This is at the present time a cutting-edge result. PreLearn appears very promising for obtaining high acceleration rates in parallel MRI even if the work is still in progress.

References: [1] Sodickson and Manning. MRM, 1997, 38:591-603. [2] Pruessmann et al. MRM, 1999, 42:952-962. [3] Griswold et al. MRM, 2002, 47:1202-1210.