NON UNIFORMITY CORRECTION USING COSINE FUNCTIONS AND TOTAL VARIATION CONSTRAINT IN MUSCULOSKELETAL NMR IMAGING

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Introduction: In this work, we attempted to correct the non-uniformities generated in lower limbs (calf and thigh) NMRI by RF inhomogeneities. Correction techniques are based in general on prior knowledge about the intensity distribution inside tissues (or tissue magnetic properties) which is not straightforward in case of pathological muscles, as in neuro-muscular disorders. For our application, we can rely only on the assumption of signal uniformity in the subcutaneous fat and we need to estimate the non uniformity values in muscles. An interpolation technique like spline or polynomial would not be efficient because the muscle area is large relative to fat. Parametric models are an attractive solution to the problem. Based on the observation that the non uniformity field is a low frequency signal, we expressed it as a finite sum of discrete cosine functions. The estimation of the parameters of the non uniformity field was done through the minimization of a convex cost function.

Theory: A convenient way of designing a correction method consists in modeling the intensity non uniformity as resulting from a smooth multiplicative field. Hence we can write : $I(v)=U(v)B(v)+n(v)$ where *v=(x,y,z)* refers to a voxel location, I the observed MRI volume, U the uncorrupted one, B the non uniformity field and n is the noise. Knowing that the non uniformity field is a smooth function, we can approximate it by a finite sum of cosine discrete functions. The choice of the cosine functions is motivated by the fact that they represent a discrete orthogonal basis. Hence we can define the non uniformity field as the following:

$$B(v)=\sum_{k_x=0}^{n_x-1}\sum_{k_y=0}^{n_y-1}\sum_{k_z=0}^{n_z-1} h_{k_x,k_y,k_z} C_{k_x}(x)C_{k_y}(y)C_{k_z}(z) \qquad C_{k_d}(d)=\cos\left(\frac{\pi(2d+1)k_d}{2L_d}\right) \quad \text{with} \quad d\in\{x,y,z\}$$

The estimation of the non uniformity field amounted to computing the vector $h=(h_{0,0,0},h_{1,0,0},\ldots h_{n_x,n_y,n_z})$ of coefficients of the cosine functions. Under the assumption that the signal in the subcutaneous fat region (noted Ω_{sf}) was uniform and that it can be approximated by its mean value (called μ_f). The estimation can be performed by minimizing the following quadratic cost function [1]: $E(h)=\sum_{v\in\Omega_{sf}}\left\| I(v)-\mu_f B(v) \right\|^2$

The efficiency of such an approach is highly dependent on the domain Ω_{sf}. The non homogeneity field can be reconstructed if the observed samples are uniformly distributed in the image domain. This was not the case of our application where the hypothesis of signal homogeneity was valid only for subcutaneous fat. The system obtained using only pixels of subcutaneous fat area was badly conditioned because the restriction of the cosine functions to this domain is no longer orthogonal. Very important oscillations were observed in the regions that were not sampled. To overcome this problem we considered an additional constraint that aimed at reducing the oscillations of the non-uniformity field. Such a constraint can be modeled by the total variation of this function. Thus, we estimated the cosine functions coefficients by minimizing the following cost function: $E(h)=\sum_{v\in\Omega_{sf}}\left\| I(v)-\mu_f B(v) \right\|^2+\lambda\sum_{v\in\Omega}\left\|\nabla B(v)\right\|^2$. The second term is the total variation of the field in the entire domain. Its role was to reduce the oscillations in the resulting function. λ is a parameter that defines the trade-off between the two constraints. The proposed cost function is convex and the optimal value of h were obtained using a gradient conjugate approach.

Exerimental validation We evaluated the performance of the proposed approach and compared the results to the method introduced in [1], which is the same as our approach when $\lambda=0$. The images we used are acquired on a 3.0 T whole body scanner (Trio TIM, Siemens Healthcare) using a circularly polarized coil.

Phantom data : 2D images of a water phantom were acquired using a standard FLASH 2D PDw sequence (TR=7s, TE= 4.92 ms, rf flip angle=45°) We imposed the uniformity constraint only on a peripheral region and then evaluated the coefficient of variation in a central region of the phantom. The results reported in table [1] showed that a high number of cosine functions better approximated the non-uniformity function. We noticed also that for higher value of k, method [1] results in important oscillations due to the bad conditioning of the linear system. Such a limitation was overcome using our constrained model.

Dixon Images: 3D PDw extended 2 pt Dixon images (TR=10ms, TE1=2.45 ms TE2=3.675 ms , rf flip angle =10°) were acquired in thighs of 4 healthy subjects. To estimate the parameters of the non-uniformity field, we segmented the subcutaneous fat in the fat image (using a simple thresholding). Then, we used the estimated non-uniformity field to correct water images. To quantify the performance of the approach, we computed the coefficient of variation (CV) on the subcutaneous fat region in the fat volume (CvF) and on the muscle region in the water volume (CvM). Table [2] shows the CVs obtained for different values of λ. Introducing the total variation term, led to a more uniform intensity inside the muscle (although this region was not used in the estimation). A normal case example is given in figure [2]. Regarding pathological cases, figure [3] obtained in a congenital dystrophic patient, illustrates that our method is adapted to normalize fatty infiltrated muscle intensity using the information of the fat image in the subcutaneous fat area.

	CvF (Peripheral area)		CvM (Central area)	
k	$\lambda=0$	$\lambda=1e3$	$\lambda=0$	$\lambda=1e3$
3	0.038	0.0405	0.0584	0.0468
5	0.0127	0.0302	0.0570	0.049
7	0.0122	0.0161	1.9828	0.0444

Table1 *Coefficient of variation using our method and the method introduced in [1] for the phantom*

	CvF				CvM			
	before	0	100	1000	Before	0	100	1000
data1	0.378	1.1998	0.2624	0.2951	0.231	1.1543	0.3222	0.1694
data2	0.4643	13.628	7.9223	0.3366	0.1664	0.3242	0.2612	0.1003
data3	0.525	51.349	4.4301	0.39	0.2617	4.7851	0.4738	0.1392
data4	0.4852	242.98	1.1327	0.3829	0.2542	19.445	0.3459	0.1644

Table2. *Coefficients of variation computed on corrected image using different values λ for (k=4)*

Figure 1. *Example of correction of a phantom from left to right (i) image before correction and the corrected images using (ii) ($\lambda=0$ and k=7) (iii) ($\lambda=1e3$ and k=7)*

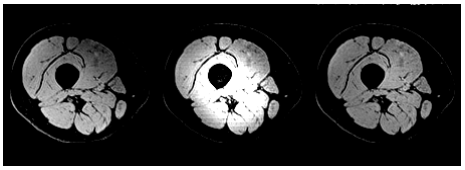

Figure2. *An example of a 2D slice of the thigh muscle (data3). From left to right values (i) water image before correction (ii) Correction using ($\lambda=0$) (iii) Correction using ($\lambda=1e3$)*

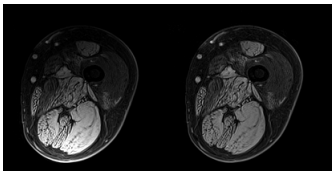

Figure3. *An example of thigh muscles water image in a congenital dystrophy patient: before correction (left) and after correction (right)*

References [1] O. Friman, et al, "A general method for correction of intensity inhomogeniety in two point dixon imaging," p 4637, in ISMRM, 2009.