A 3D Parametric Model for Imaging Normalization

Tiejun Zhao[1], and Kwan-Jin Jung[2]

[1]*Siemens Healthcare USA; Siemens Medical Solutions USA, Inc., Pittsburgh, PA, United States,* [2]*Psychology, Carnegie-Mellon University, Pittsburgh, PA, United States*

Introduction: Multi-channel receiving (Rx) coils have become a standard asset of routine MR imaging due to its improved signal-to-noise ratio and the parallel imaging capabilities. However, the image intensity variations from the receiving profile could be problematic for tissue segmentations and various quantification analyses[1-4]. While the pre-scan normalization that acquires additional data using body coil provided a popular approach for removing this imaging shading artifact, a retrospective normalization can still be invaluable especially when the extra data is not available due to various reasons (e.g., the original protocol did not include a pre-scan for normalization or a uniform body coil is not available for some head only scanners or current most 7T scanners.) In this abstract, we proposed and demonstrated a simple 3D parametric model for modeling and removing the smooth image intensity variations presented in images acquired with multi-channel Rx coil.

Methods: In this proposed method, we are assuming that the image intensity from the multi-channel receiving coil can be described by the following smooth heuristic model for any given slice,

$$I(x,y) = A(z)\{1-\exp[-R_x(z)(x-x_0(z)]^2 - R_y(z)[y-y_0(z))^2]\} + B(z)$$

where *I(x,y)* is the image intensity at a slice location z. For a single slice, the z is fixed and thus fitting can be carried out with the standard non-linear optimization routine provided by Matlab with 6 unknown parameters. While x_0 and y_0 define the center position of the Rx profile, R_x and R_y are the radius of the Rx profile along x and y directions that control the steepness of the Rx shading for a given coil.

The $R_x(z)$, $R_y(z)$, $x_0(z)$ and $y_0(z)$ were assumed to be only linearly depend on the z. For example, $R_x(z) = R_x(1-k_xz)$ where k_x is the corresponding constant that determines how the R_x can be changed along z.

Similar to x, y, we assumed,

$$A(z) = A(1-\exp(-R_{z1}(z-z_0)^2))$$

$$B(z) = B(1-\exp(-R_{z2}(z-z_0)^2))$$

where z_0 defines the center position of Rx profile along z-direction and R_{z1} and R_{z1} are constants that controls how the Rx profile along z is varied. With all these expansions, the 3D parametric model contains total 12 unknowns. The fitting procedure was carried out with following steps. First, creating a mask for removing the skull and the CSF based on image intensity. An accurate segmentation is found to be unnecessary due to the subsequent fitting process in the second and third steps. Second, fitting selected slices (middle 8 slices for this manuscript) to the 2D model to obtain the initial parameter sets of A, R_x, R_y, x_0, y_0 and B and use those as the initial guess for the subsequent 3D fitting. Third, taking the above initial set (all other unknowns are assumed to be zeros) as the starting point for the 3D optimization. For the data presented here, we had 8 different initial sets and the 3D non-linear optimization was carried out 8 times. The final result was selected among the 8 fittings that has the minimal residual error.

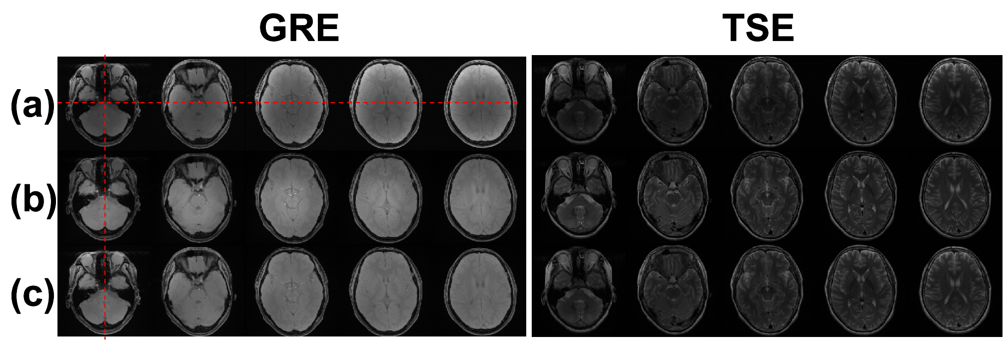

Fig. 1 Selected GRE and TSE slices. (a) sum-of-square (SOS) images, (b) pre-scan normalized images, and (c) normalized images using proposed method.

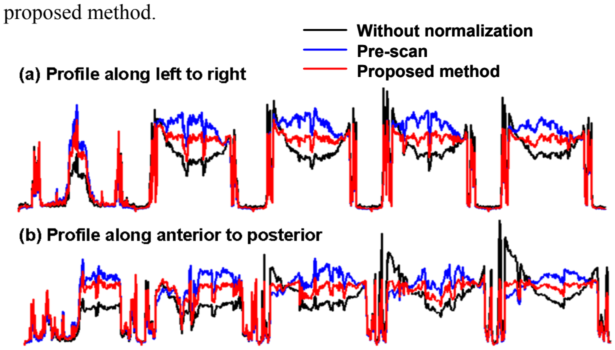

Fig. 2 1D slice profiles at the middle position (dotted line)

Results and Discussion: All experiments were carried out on the 3T Siemens Verio scanner (Erlangen, Germany) with both 12-channel and 32-channel receiving arrays. The 2D multislice 256x256 GRE images were acquired with FOV = 205mm, Flip Angle = 30°, TR = 400ms, TE=4ms and slice thickness = 3.2mm. The 2D multislice 256x256 T2 TSE images were acquired with FOV = 205mm, TR = 5200ms, TE=87ms and slice thickness = 3.2mm. A total of 20 slices that covered the whole brain were acquired for both scans. Fig.1 shows 5 slices that are evenly selected out of total 20 slices from the GRE and TSE results The Rx shading pattern that is brighter at the peripheral region and darker at center was evident for the un-normalized GRE images (Fig.1 (a)). The pre-scan normalization results shown in Fig.1 (b) removed Rx shading profile with the transmit (Tx) profile unaltered, which exhibited as slightly brighter in the brain center as expected. On the contrary, the proposed method (Fig.1 (c)) alleviated the shading artifacts from both Rx and Tx, which led to a flatter imaging profile than the pre-scan normalized method. Another noticeable shading artifacts for un-normalized sum-of-square (SOS) images is along slice direction, which was shown as decreased image intensity toward feet direction. Both the pre-scan normalization and the proposed normalization method reduced this shading artifact. To better illustrate the problem and improvements, the 1D profile along both left-right and anterior-posterior (for the dotted red line in Fig.1) for all 5 selected slices were shown in Fig.2. It is clear from these 1D profiles that the proposed method provided more uniform images. However, the new method does have slight residual shadings in the left-right direction (especially for lower slices) that will need further improvement. The TSE images, on the other hand, demonstrated much milder shading except along the slice direction. The pre-scan normalized and the 3D fitting model both seemed to adequately remove this artifact. The results (data not shown) of the corresponding 12-channel Siemens head matrix also exhibited mild shading and improvements from the proposed methods is similar to those TSE cases presented here, that is the improvement is mainly along slice direction.

The total 3D nonlinear fitting routine for both GRE and TSE took about 5min on a Dell PC with two dual core 2.3GHz CPU and 2.0G RAM. Note that the optimization was carried out 8 times with different initial parameters estimated from a 2D fitting.

Conclusion: The proposed method successfully reduced the imaging shading for both Siemens 12 and 32 channel receiving coils. Compared to the standard pre-scan normalization method, this retrospective method also seemed to remove some of the excitation profiles and provided a feasible way for retrospective image normalization. We might be able to reduce the 3D optimization routine to well less than 1min for a given coil once the initial parameters' range is studied and determined, which will potentially allow us to avoid the guess of the initial parameters. The advantage of 3D normalization when compared to a 2D normalization is to ensure smooth transition of the image intensity after correction.

References: [1] B. Belaroussi, et al., Medical Image Analysis 10 (2006) 234–246. [2]U. Vovk, et al., IEEE TRANSACTIONS ON MEDICAL IMAGING, VOL. 26, NO. 3, MARCH 2007. [3]F. Kremers,, et al., JOURNAL OF MAGNETIC RESONANCE IMAGING 31:227–233 (2010). [4] R. Guillemaud, et al., IEEE TRANSACTIONS ON MEDICAL IMAGING, VOL. 16, NO. 3, JUNE 1997