AN A-PRIORI SUPPORTED IMAGE CORRECTION METHOD FOR SEVERE INTENSITY NON-UNIFORMITIES AT 3 T

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Introduction: Despite its diagnostic capabilities, MRI can be used to quantify a vast variety of features, such as volumes of entire or partial organs (e.g. brain, liver, etc.) or different tissue compartments. Many segmentation algorithms have been proposed to accomplish automatic image segmentation, of which the most commonly used are procedures based on histogram thresholding. Image non-uniformities (INUs) caused by B_1 inhomogeneities as well as spatially dependent coil sensitivity are a major concern when fully- or semi-automated thresholding procedures are used. These effects become ever more critical at high field strengths [1]. Many procedures have been proposed to compensate for these effects, including histogram sharpening [2], adaptive clustering algorithms [3] or reference measurements with uniform phantoms [4]. The first two cannot compensate for strong INUs, which are common for abdominal image slices at 3 T, and the latter requires additional image acquisitions. The purpose of this work was to develop and test an algorithm being able to compensate these strong INUs by exploiting anatomy.

Materials and Methods: Intensity non-uniformities are usually modeled as a smoothly varying, multiplicative bias field $B(\boldsymbol{x})$, which corrupts an ideal image $I_i(\boldsymbol{x})$ to the actually obtained image $I_o(\boldsymbol{x}) = I_i(\boldsymbol{x})\cdot B(\boldsymbol{x})$. Thus, the compensation process can be reduced to an estimation of the underlying bias field from the obtained image. This approach proposes to estimate the bias field from the ring of subcutaneous adipose tissue (SCAT). A fuzzy c-means (FCM) algorithm is used to pre-segment the image into body and background. This procedure is usually possible even in heavily corrupted images. The outer body contour is then refined using an active contour algorithm. Then, another active contour algorithm with additional deflation forces is used to detect the inner boundary of the SCAT ring. The intensity of the obtained SCAT area is then sampled at a number of nodes and a first estimation of the bias field is obtained by fitting these nodes with a cubic spline surface. After correcting the image with this first estimation, it is also possible to use AT areas deeper inside the body for a further refinement of the bias field estimation. Therefore, all areas inside the body, which are brighter than 0.7 times the mean SCAT intensity, are considered as additional nodes for the cubic fitting spline. Using these nodes and the nodes in the SCAT area, the final bias field estimation is fitted and the compensated image is calculated.
To validate the proposed algorithm, both, artificial and real data was used. The abdominal area of a normal weight volunteer was imaged on a 1.5 T and on a 3 T system on the same day. On each scanner, a dataset of 20 axial, T1-weighted images was acquired. An existing segmentation algorithm, which reliably separates and quantifies lean tissue and adipose tissue based on an FCM clustering in 1.5 T datasets, was applied on the original 1.5 T images, the original 3 T images and the corrected 3 T images and the obtained tissue areas were compared. To get quantitative measures of the decrease of in-class standard deviation due to the correction and the amount of INU after correction, two representative abdominal image slices were manually segmented into the predominant tissue classes (see Fig. 1a and 1b). The images were then corrupted (multiplied) by a random bias field, obtained by assigning random values to a Cartesian grid of nodes and interpolating the surface in between the nodes using a cubic spline interpolation. The resulting bias field was then scaled to intensity range [0.1, 1], simulating up to 90 % of INU. The spacing of the nodes (which determines the highest possible spatial frequency in the bias field) was chosen to correspond to half the wavelength of the 1H RF-signal in the body (about 130 mm). Afterwards, the decrease in in-class standard deviation (divided by the class's mean to compensate for intensity scaling) and the INU after correction for each class was measured.

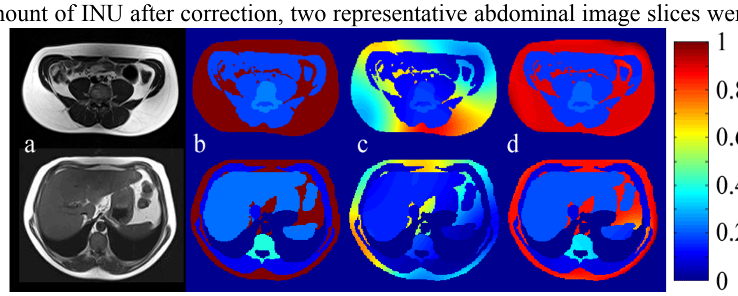

Figure 1: Artificial slices, corruption with INU and correction.

Results: Fig. 2b shows the unsatisfying result of an FCM clustering algorithm on the 3 T abdominal image slice in Fig. 2a; Fig. 2c shows the much better result of the same algorithm, performed on the corrected image. A comparison of the obtained volumes of lean tissue and adipose tissue in the 1.5 T and 3 T dataset showed a very good correlation with a 4.19 % lower lean tissue volume and a 1.41 % higher adipose tissue volume in the 3 T dataset compared to 1.5 T.
In the evaluation with artificial images, each image was corrupted using ten randomly created bias fields and corrected afterwards. In the first image, the standard deviation of lean tissue areas was at an average reduced by factor 37.85, in the vertebra class by factor 17.12 and in the adipose tissue class by factor 35.06. In the second image, the muscle class showed a decrease in standard deviation by factor 15.22, in the class of parenchyma organ by factor 9.50, in the vertebra class by factor 6.16 and in the adipose tissue class by factor 23.13. In image 1, the amount of INU (up to 90 % in the corrupted images) could at an average by reduced to 4.44 % for the class of lean tissue, 2.15 % for vertebra and 8.10 % for adipose tissue. In the second image, the amount of INU could be reduced to 13.11 % for the muscle class, 15.46 for the class of parenchyma organs, 9.46 % for vertebra and 12.28 % for adipose tissue.

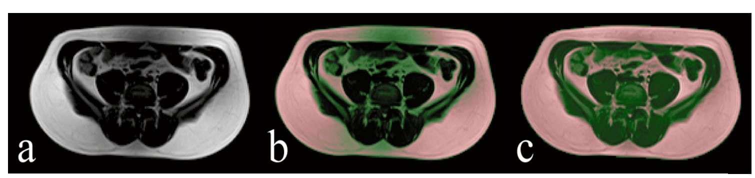

Figure 2: a) original image **b)** result of FCM on original image **c)** result of FCM on corrected image.

Conclusion: Due to the increasing amount of intensity non-uniformities, present in MR images at high field strengths and the emerging of quantitative MR techniques, the need for robust inhomogeneity compensation algorithms is growing. We propose a reliable algorithm for non-fat-suppressed techniques, which is backed by involvement of anatomic information. The algorithm showed good results on both, simulated and artificial data. Its capability to correct even strong INUs enable the use of simple thresholding techniques even on abdominal images acquired at 3 T.

[1] F. Schick, *Eur Radiol* 2005:15:946-959. **[2]** O. Salvado et al., *IEEE Trans Med Imaging* 2006:25:539-552. **[3]** D. Pham et al., *IEEE Trans Med Imaging* 1999:18:737-752. **[4]** A. Viddeleer et al., *Magn Reson Mater Phy*, 2009:22:201-209.