

Fat Water Classification of Symmetrically Sampled Two-Point Dixon Images Using Biased Partial Volume Effects

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Introduction: Symmetrically sampled two-point Dixon images (1) reconstructed using phase sensitive reconstruction (PSR) result in fat and water images. Due to the fat-water-phase symmetry it is impossible to automatically identify which image is which only based on the phase information. Thus the fat/water identities are unknown after PSR. Since the identity are vital during post processing such as chemical shift correction and fat quantification the data have to be classified post PSR.

Recently a method utilizing the intensity difference caused by the bimodal chemical shift spectra of fat has been proposed (2). We propose an alternative method based on the bias created in partial fat-water volumes due to tissue intensity differences. The method is motivated by a very simple signal model and it was validated on 905 tissue volumes, excluding training and undefined data.

Materials and Methods: The data were acquired using a 1.5 T Philips Achieva MR-scanner (Philips Medical Systems, Best, The Netherlands). In and out of phase images were obtained using the echo timed 2.3 and 4.6 ms, the repetition time TR was set to 6.57 ms and the flip angle to 13 degrees. The PSR was performed in 3D using the previously reported inverse gradient method (3,4).

Data from two different studies were used for the evaluation. The first image volumes consisted of pre and post Gd-EOB-DTPA injections on 45 patients (405 tissue volumes in total) and the investigations covered the liver. The volumes were captured in 3D during a single breath hold using a SENSE body coil. The second set of tissue volumes were whole-body datasets from 50 patients (584 tissue volumes in total) acquired using the quadrature body coil.

It is possible to calculate the mean intensity of the partial volume voxels assuming that the fat and water intensities are homogenous on a macroscopic scale and that the fat/water ratio of a partial volume is evenly distributed. The average contribution of each signal in a partial volume then becomes half the mean fat and water intensities m_f and m_w . Thus the intensity will be biased towards fat or water if their means differ. This bias is then studied using an artificial out of phase image volume $OP = (w - f)/(m_f + m_w)$, where w and f are the fat and water volumes. The means are used to shift partial volume effects to the intensity range $\sim[-0.5, 0.5]$. Analysis of the data showed m_f to be close to $2m_w$ for the pre-contrast volume, but the difference decreased after contrast injection. This gave an intensity of $-1/3$ for the average partial volume in OP (pre-contrast). Thus it was possible to evaluate if $OP=w-f$, or if $OP=f-w$ by studying the distribution of intensities close to 0.

PSR resulted in the two image volumes I_1 and I_2 , of which one was the water volume and the other the fat volume. The artificial out of phase volume was created by $OP=(I_1-I_2)/(m_{I_1}+m_{I_2})$. If the distribution close to 0 was shifted towards negative intensities $OP=w-f$, and vice versa.

The discriminating vector c was calculated using 'Linear Discriminant Analysis' (LDA) (5) on a set of intensity frequency spectra (normalized histograms) from OP volumes with randomly ordered, but known, fat and water identities.

A volume can contain more than one tissue object separated by air. Since air cannot carry any phase information due to noise this sometime result in a mix-up of fat and water between non-connected tissue objects. To avoid this connected component labelling was used in order to identify objects and then to classify them individually.

Results: Contrast data was obtained from 9 patients, corresponding to a total of 78 tissue volumes, were selected as training data for LDA. A mask was applied in order to exclude noise from h . The mask was created using Otsu's method (6) on $f+w$. Only the OP intensities in the range $[-0.5, 0.5]$ were used. The discriminating vector c is shown in Fig. 1.

Visual identification by a human reviewer was used as a golden standard. Upon visual classification, one single volume was excluded from the evaluation since it contained water and fat objects that the connected component labelling could not separate. The classifier correctly classified all remaining volumes.

Discussion and Conclusions: The advantage of using partial volumes was clearly demonstrated. In addition, we expected that the results to some extent would be affected by different MR-scanner settings, but the procedure was demonstrated to be very robust. Another observation of great importance was that the method has shown to work as intended also in the presence of contrast agents, which will induce large local signal changes of the water signal in affected parts of the tissue. The signal model does not take into account the water signal content of adipose tissue, a factor that will decrease the bias slightly toward the fat mean, however this did not appear to influence the results.

The procedures were successfully carried out on data that were more than ten times larger than the training datasets. This allowed both for whole body coverage, and also for abdominal examinations using contrast agents. Since some volumes contained more than one object, and thus was split up before the classification, the number of correctly classified objects was much larger than the number of volumes in the evaluation. A typical example of the classification result is shown in Fig. 2, showing how fat and water volumes goes from an unordered state to an ordered one even though mix-ups exist within single volumes (see the top two volumes).

References: 1. Dixon W. Radiology 1984;153(1):189-194. 2. Ahmad M, Liu Y, Slavens Z, et al. Magn Reson Imaging 2010;28(3):427-433. 3. Rydell J, Knutsson H, Pettersson J, et al. Med Image Comput Comput Assist Interv 2007;10(Pt 1):210-218. 4. Rydell J, Johansson A, Leinard OD, et al. Proceedings of ISMRM'08; 2008. p. 1519-. 5. Fisher RA. Annals of Eugenics 1936;7(2):179-188. 6. Otsu N. Systems, Man and Cybernetics, IEEE Transactions on 1979;9(1):62-66.

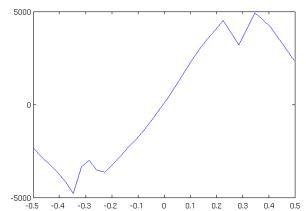


Fig. 1. The discriminating vector c , the weight for a frequency h is given on the y -axis

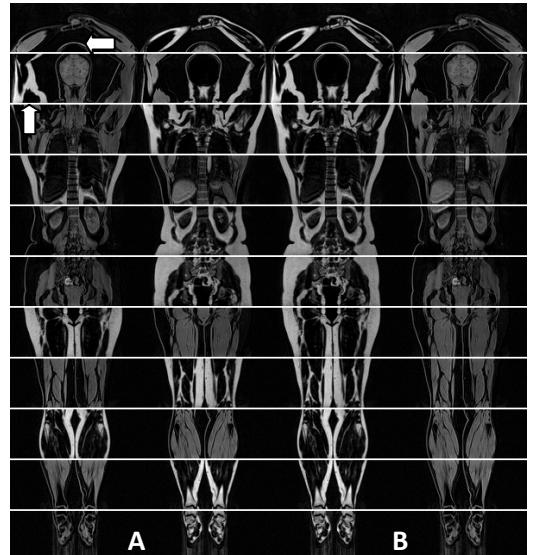


Fig. 2. Before and after fat water classification, different volumes are separated by a white line. After the PSR (A) the identities are unknown. After classification (B) the fat/water volumes have been grouped. The top two volumes show how non-connected tissue of the arm and top of head, with inverse fat/water content compared to the rest of the volume, has been correctly classified.