# Histogram based water and fat identification in a symmetrically sampled dual echo Dixon technique

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### Introduction:

Dixon techniques [1] offer potential for excellent water and fat separation and can be implemented with a wide variety of sampling strategies and pulse sequences. Among them, the symmetrically-sampled dual-echo Dixon technique [2,3] (by which two echoes with water and fat in-phase and 180° out-of-phase are acquired after a single RF excitation) possesses several appealing advantages. First, its acquisition time can be as short as or even slightly shorter than that of a regular protocol with more conventional fat suppression and similar scan parameters. Second, its SNR performance is the highest relative to the other asymmetrically-sampled Dixon techniques and is independent of the relative water and fat ratio in a given pixel. Thirdly, the symmetric sampling offers the largest angular separation between the water and fat signals and thus the highest processing reliability in the presence of image noise and artifacts.

One potential technical difficulty for the clinical implementation of the symmetrically-sampled dual echo Dixon technique, however, is the identification of the water and fat images after they have been separated. Such identification is needed for correct image annotation and was previously assumed to be impossible in the case of symmetric sampling [4]. In this work, we propose and demonstrate that the goal of an automatic and reliable water and fat identification can be achieved with a histogram based approach.

### **Experiments and Method:**

All data were acquired with a 3D symmetrically-sampled dual echo fast spoiled gradient echo pulse sequence [3] on 1.5T and 3.0T GE whole body MRI scanners (GE Healthcare). The first echo and the second echo correspond to a water and fat relative phase of 180° and 0, respectively. A total of fourteen 3D abdomen/pelvis patient datasets were used to test the water and fat identification algorithm (see below). Both axial and coronal acquisitions were used in the testing. Patient habitus ranged from being very lean to very fat. In all cases, an 8-channel phase-array coil was used for data collection. Water and fat separation was achieved using an automated phase correction algorithm that was implemented on the scanners' product platform [2-3]. All the images corresponding to a given chemical species (i.e. water or fat) from different spatial slices in a 3D volume were automatically grouped into a given image series by using a previously published slice-to-slice correlation algorithm [5].

The algorithm we propose for water and fat identification is based on the observation that the highest signals in an image intensity histogram belong in general to the fat pixels. The algorithm thus works by first finding  $I_{max}$ , the maximum intensity of  $I_1$  and  $I_2$  that are the two images to be identified as either water or fat. As the second step,  $SUM_1$  and  $SUM_2$ , the intensity sum of all the pixels in  $I_1$  and  $I_2$  that have an intensity value greater than a chosen fraction ( $\alpha$ ) of  $I_{max}$ , are calculated. As the identification criterion,  $I_1$  is designated as water if  $SUM_1$  is less than  $SUM_2$ . Otherwise,  $I_1$  is designated as fat if  $SUM_1$  is greater than  $SUM_2$ . For a given 3D data set, the algorithm is applied to only the very central slice since the slice-to-slice correlation algorithm ensures consistent water and fat identification throughout the volume [5]. **Results:** 

# With $I_1$ designated as water and $I_2$ designated as fat (using the visual inspection as the reference standard), Table 1 lists $SUM_1$ and $SUM_2$ (both normalized by $I_{max}$ ) for the central slices of all the datasets using an empirical $\alpha$ value of 0.9. The proposed algorithm can easily identify water and fat correctly in all the cases because most of the $SUM_1$ is zero. For the only slice (patient #10) for which $SUM_1$ is non-zero, $SUM_2$ is still several times bigger than $SUM_1$ . Fig. 1 shows the water-only and fat-only images for the corresponding slice.

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Patients #	1	2	3	4	5	6	7	8	9	10	11	12	13	14
SUM <sub>1</sub> (water)	0	0	0	0	0	0	0	0	0	44	0	0	0	0
SUM <sub>2</sub> (fat)	15	15	1580	589	355	428	22	1750	380	167	312	1600	518	602



The algorithm is also found to work for the non-central slices of all the data sets except for a few edge slices in the two datasets (#1 and #2) of a very lean subject (an elite athlete). The variation in the spatial placement of the 3D volume is thus not expected to affect the performance of the algorithm. Table 2 displays the  $SUM_1$  and  $SUM_2$  (again normalized by  $I_{max}$ ) for the images in Fig. 1 as a function of  $\alpha$ . Similar data trends are observed in other data sets. The algorithm is therefore also very insensitive to the exact choice of the  $\alpha$  value.

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α	0.7	0.75	0.8	0.85	0.9				
SUM <sub>1</sub> (water)	61694	7457	949	95	44				
SUM <sub>2</sub> (fat)	122033	31864	9491	1559	167				

Fig.1. For the only patient with non-zero  $SUM_1$ ,  $SUM_2$  (fat, right) is still several times greater than  $SUM_1$  (water, left).

### **Discussions and Conclusion:**

We proposed and showed that after water and fat separation, a purely histogram based approach can be used to correctly identify the images that are acquired in abdomen/pelvis and using a symmetrically sampled dual echo fast spoiled gradient echo Dixon technique. Such a task was previously deemed impossible using only the phase information. Although not extensively evaluated, the algorithm may also be applicable to the images of other anatomic regions or images acquired with other symmetrically sampled Dixon techniques.

### Acknowledgements:

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## **References:**

[1] Dixon WT, Radiology 153:189, 1984. [2] Ma J, MRM 52:415, 2004. [3] Ma J, et. al., JMRI 23 :36, 2006. [4] Xiang QS, et. al., JMRI 7 :1002, 1997. [5] Ma J, et. al. MRI 23 :977, 2005.