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A method for automatic identification of water and fat images from a symmetrically-sampled dual-echo Dixon technique

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Abstract

Sampling water and fat signals symmetrically (i.e., at 0 and 180° relative phase angles) in a dual-echo Dixon technique offers high intrinsic tolerance to phase fluctuations in postprocessing and maximum SNR performance for the separated water and fat images. However, identification of which image is water and which image is fat after their separation is not possible based on the phase information alone. In this work, we proposed a semi-empirical automatic image identification method that is based on the intrinsic asymmetry between the water and fat chemical shift spectra. Specifically, the approximately bi-modal feature of the fat spectra and the observation that most in vivo tissues are either predominantly water or predominantly fat are used to construct a spectrum-based algorithm. Additional refinement is accomplished by considering the spatial distribution of the tissues that may have a coexistence of water and fat. The final improved algorithm was tested on a total of 131 three-dimensional patient datasets collected from different scanners and found to yield correct water and fat identification in all datasets.

Keywords

Dixon imaging; symmetric sampling; water and fat identification; fat spectra

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Introduction

Dixon techniques (1-4) can provide uniform water and fat separation that is insensitive to the magnetic field inhomogeneity and that can be implemented with a wide variety of pulse sequences. Among the different implementation strategies, the symmetrically-sampled dual-echo Dixon technique (5,6) (by which two echoes with water and fat signals in-phase and 180° out-of-phase are acquired with two consecutive readout gradients of alternating polarity after a single RF excitation) possesses several appealing properties. First, the acquisition time can be as short as or even slightly shorter than that of a corresponding non-Dixon pulse sequence with similar scan parameters but more conventional fat suppression. Second, the SNR of the final water-only and fat-only images is 2 times the SNR of the in-phase and out-of-phase images and is highest when compared to an asymmetrically-sampled Dixon technique (7). Finally, the symmetric sampling provides the largest angular separation between the water and fat signals (i.e., 180°), which is always helpful for increased postprocessing reliability during the determination and removal of the additional random fluctuations in the signal phase (such as from noise and artifacts) (4).

One technical difficulty for a fully-automated implementation of the symmetrically-sampled dual echo Dixon technique, however, is the identification of which image is water and which image is fat after the two images have been separated. Correct image identification is a pre-requisite for proper image annotation and for selecting which images to archive.

Identification of the separated water and fat images is also necessary when the images are used for automatic generation of fat-to-water ratio maps or for correction of fat chemical shift artifacts along the frequency encode direction. Although seemingly trivial by visual inspection, automatic identification of water and fat images from a Dixon technique with symmetric sampling has been deemed impossible based on the phase information alone and the challenge is described as analogous to “the difficulty in unambiguously determining how the two hands on a clock rotate if they are only observed at either the parallel or anti-parallel positions” (3,7). A possible workaround to resolve the difficulty is to exploit the intensity histogram difference between the water and fat images after they are separated (5,8). Similar approaches have been reported for the problem of water and fat identification in phase sensitive steady-state free-precession (9) or in restoring the intrinsic signal polarity for phase sensitive inversion recovery imaging (10,11). However, the image intensity characteristics are subject to many variations in a scan protocol as well as the anatomy being imaged. While evaluating a product implementation of the symmetrically-sampled dual echo Dixon technique with different scan protocols and in a large number of patients, we found that a purely histogram based method for automatic image identification may fail in certain situations, particularly when the images were acquired after the intravenous injection of contrast agent.

In this work, we propose a semi-empirical but fully-automated image identification method by exploiting the intrinsic asymmetry between the water and fat chemical shift spectra. The method is based on the fact that the actual shape of the fat spectra is approximately bi-modal in comparison to a single peak for the water resonance and on the observation that most in vivo tissues are either predominantly water or predominantly fat. The method is further refined by considering the spatial distribution of the tissues that may have a coexistence of

water and fat. We evaluated a final improved implementation of the method in a total of 131 three-dimensional patient datasets collected from different scanners. In comparison to a purely histogram based approach, the new method is found to be much more reliable in correctly identifying the separated water and fat images.

Methods and Materials

Assuming that the two magnitude images after the water and fat separation are represented by $I_1(x,y)$ and $I_2(x,y)$, where x and y stand for the two spatial coordinates of the image pixels. The problem of water and fat image identification is to determine which of $I_1(x,y)$ and $I_2(x,y)$ is water and which is fat. The separation of water and fat or derivation of $I_1(x,y)$ and $I_2(x,y)$ from the complex in-phase and out-of-phase images of a symmetrical dual-echo acquisition is a separate problem and can be achieved after removing the magnetic field inhomogeneity effect with a phase correction algorithm such as described in Ref.(5,6). Since the raw images are acquired symmetrically and $I_1(x,y)$ and $I_2(x,y)$ are magnitude-only, a phase-based method (such as that in Ref. (3) or (7)) cannot be used on $I_1(x,y)$ and $I_2(x,y)$ for the purpose of image identification.

An implicit assumption for many Dixon techniques is that fat has a single resonance peak that is approximately 3.5 ppm away from the single water resonance. While the model of a single peak for the fat resonance is a good approximation for water and fat separation, it is well-known that the actual chemical shift spectrum of fat consists of contributions from protons in the triglycerides with many different chemical environments (4,12). What is typically considered a single fat spectral peak at 3.5 ppm (relative to water) actually represents contribution from several different moieties with slightly different resonance frequencies, including the methylene protons and terminal methyl groups. Another noticeable contribution to the fat spectrum is the olefinic protons whose resonance falls very close to that of water (with a separation of approximately 0.5ppm). Consequently, signals from this resonance will appear as “water” signals (4) when the water and fat separation is achieved by assuming a single peak model for both water and fat. Although the exact intensity of an image pixel is dependent on the relaxation and the scan parameters, the contributions from the olefinic protons will in general result in a finite signal intensity for pixels with even only fat in the water-only image. In contrast, pixels with only water are expected to have zero signal intensity in the fat-only image.

Exploiting this signal disparity and the observation that most in vivo tissues are either predominantly water or predominantly fat, we designed the following 3-step process for water and fat image identification. The algorithm is semi-empirical but fully automated:

1. The first step is to create a mask image that thresholds out pixels in $I_1(x,y)$ and $I_2(x,y)$ that do not contain any appreciable amount of signals. A convenient threshold value to use is 5% of the maximum intensity found in $I_1(x,y)$ and $I_2(x,y)$. The exact threshold value to be used is unimportant since the final decision is based only on a statistical calculation from all the pixels with the signals, as described below. As a result, we used a fixed threshold of 5% in our algorithm for all the data tested.

2. The second step is to create two additional mask images $M_1(x,y)$ and $M_2(x,y)$. $M_1(x,y)$ is 1 for all the pixels where $I_1(x,y)$ is greater than $I_2(x,y)$ and 0 for all the pixels where $I_1(x,y)$ is less than $I_2(x,y)$ or where they are masked as noise in Step 1. Similarly, $M_2(x,y)$ is 1 for all the pixels where $I_2(x,y)$ is greater than $I_1(x,y)$ and 0 for all the pixels where $I_2(x,y)$ is less than $I_1(x,y)$ or where they are masked as noise in Step 1.
3. The third step is to determine two parameters A_{21} and A_{12} from the two images $I_1(x,y)$ and $I_2(x,y)$, and the two masks $M_1(x,y)$ and $M_2(x,y)$. A_{21} is the average value of the product image $I_2(x,y) \cdot I_1(x,y)$ calculated over all the pixels masked by $M_1(x,y)$. Similarly, A_{12} is the average value of the product image $I_1(x,y) \cdot I_2(x,y)$ calculated over all the pixels masked by $M_2(x,y)$.

Based on the asymmetry between water and fat spectra, we make the binary decision by assigning $I_1(x,y)$ as the water-only image and $I_2(x,y)$ as the fat-only image if A_{21} is smaller than A_{12} . Otherwise, we assign $I_1(x,y)$ as the fat-only image and $I_2(x,y)$ as the water-only image.

The above decision process is based on the assumption that excluding pixels masked out as noise, a large majority of the pixels in an image are either predominantly water or predominantly fat. This assumption is valid for most in vivo imaging applications. In abdominal imaging, for example, signals from the pixels corresponding to muscle, spleen, and blood vessels are almost always purely water. In contrast, signals from pixels corresponding to subcutaneous and visceral fat are almost always purely fat. However, some exceptions may occur. For example, pixels corresponding to liver, which usually is predominantly water, may contain appreciable amounts of signals from both water and fat in the case of fatty liver. Similarly, bone marrow may have both fatty and hematopoietic components. In order to accommodate these situations, we take advantage of the fact that these tissues with a coexistence of water and fat tend to be located towards the center of an image and are always surrounded by some fat-dominant tissues (such as the subcutaneous fat). A geometric weighting that preferentially suppresses the contribution from the center of the image can be applied during the calculation of A_{21} and A_{12} to enhance the relative contribution from the tissues that are not expected to contain both water and fat. In our method, we found that $f(x,y) = \sqrt{x^2+y^2}$ (where the center of the image is defined as the spatial origin) to be a convenient and effective geometric weighting function.

Fig. 1 presents a flowchart of the algorithm described above. We implemented the algorithm in Matlab (MathWorks, Natick, MA) and evaluated its performance on 131 different three-dimensional (3D) patient datasets with a total of 13496 separated water-only and fat-only image pairs. These patient data were collected from several different scanners (both 1.5 Tesla and 3 Tesla field strengths, GE Healthcare, Waukesha, WI) during the pre-product evaluation of the dual-echo Dixon technique. Since the primary target application of the dual echo Dixon technique is presently for abdomen and pelvis imaging (13,14), we included in our evaluation both pre-contrast and post-contrast images of the abdomen and pelvis in all three different imaging planes (axial, coronal and sagittal). Independent of the field strength,

an 8-element torso phased array coil was always used and the first opposed-phase image (ca. at a TE of 1.2 ms at 3.0 Tesla) and the first in-phase image (ca. at a TE of 2.4 ms at 3.0 Tesla) were acquired for the Dixon processing. The other imaging parameters were in general similar to those reported by Low et al (13) and by Cornfeld et al (13) and were as follows: flip angle = 12°-15°, TR = 5.5–7.5ms, acquisition matrix ~ 320×192×50, field-of-view ~ 30-45cm, slice thickness ~3mm, parallel imaging acceleration factor ~ 2, and breath hold time ~18-28 seconds. These parameters were allowed to vary for different patients in order to achieve an acceptable breath-hold time. For comparison purpose, we tested the performance of a previously reported pure histogram based algorithm (8) for water and fat identification on the same set of images. As described in Ref. (8), the pure histogram-based algorithm works under the assumption that the highest signals in an image intensity histogram in general belong to the fat pixels. The sum of the signal intensity for all the pixels whose intensity is above a certain threshold (e.g., 90% of the maximum intensity) for $I_1(x,y)$ and for $I_2(x,y)$ is thus calculated. The image with the bigger sum is then assigned as the fat-only image and the image with the smaller sum is assigned as the water-only image.

In all cases, we used visual inspection as the gold standard for water and fat image identification. To quantitatively characterize the robustness of the water and fat identification algorithm, we defined and calculated for each pair of images the following parameter:

$$\alpha = \frac{A_{21} - A_{12}}{A_{21} + A_{12}} \quad [1]$$

According to this definition, α is a dimensionless parameter and its value should be independent of the image intensity scaling. Water and fat identification is correct when α is positive and incorrect when it is negative. When α is equal to or very close to zero, water and fat identification becomes indeterminate.

Result

Our testing showed that 98% of the 13496 total image pairs were correctly identified by the final improved method based on the spectral asymmetry. Without the geometric factor, the method was correct in 94.5% of the cases. In comparison, the pure histogram based algorithm had a success rate of only 41.5%. The 2% cases of failure by the final improved method were verified to be all from the edge slices of either a sagittal or a coronal 3D acquisition. These images were visually verified to be of very low signal-to-noise (SNR) and/or to contain some obvious slice aliasing artefacts. The poor quality (low SNR and aliasing artifacts) at some edge slices are generally caused by the finite transition widths in the 3D slab profile and are the main reason why a few slices (2 slices in the scanners we used) on each edge of the 3D acquisition were not even included in the output images. When applied to only the central 90% of the slices for all image datasets, the final improved method based on the spectral asymmetry easily achieved a 100% success rate. The water and fat identification failure in the 2% edge slices did not pose any practical problem because in the actual implementation, correct water and fat identification is needed only for the central slice and identification for the other slices is achieved by ensuring slice-to-slice consistency.

Such consistency was obtained through a slice-to-slice correlation index that is based on the smoothness of the magnetic field inhomogeneity along the slice direction (10,15). In our evaluation, the spectrum-based method in combination with the slice-to-slice index therefore achieved correct water and fat identification for all the images in the 131 patient datasets.

Figure 2a) shows the α -distribution from all the 13496 image pairs for the spectrum-based method with the geometric weighting. The mean α value for all the images was 0.27. In comparison, the distribution of a similarly-defined α -value for the pure histogram based method is shown in Fig. 2b). Because the pure histogram based method works according to which image contains more pixels with the highest intensity values, image identification for most image pairs is either correct (with an α -value of 1) or incorrect (with an α -value of -1). For the image pairs evaluated, most identification turned out to be incorrect with a mean α -value of -0.17 . A major source of failure in the pure histogram based method was attributed to arise from the injection of contrast agent, which preferentially causes brightening of the water-dominant pixels due to the shortening of T1. Fig. 3a) shows the water-only image from a coronal slice of a patient before the contrast agent injection. The intensity histogram for the image and the corresponding fat-only image are shown in Fig. 3b) and 3c), respectively. Because the pixels with highest signal intensities (e.g., above 1000) are almost all from the fat pixels, the pure-histogram based method worked well in this case and the value of α by the method was 1.0. The spectral-based method yielded an α value of 0.36 and therefore also worked correctly. Fig. 3d) shows the post-contrast water-only image from the same slice as for Fig. 3a). The signal intensity histogram for the image in Fig. 3d) and the corresponding fat-only image is shown in Fig. 3e) and 3f), respectively. While the intensity histogram of the fat-only image (Fig. 3f) remained largely unchanged relative to Fig. 3c), a comparison between the intensity histograms of the water-only image (Fig. 3e) and the fat-only image (Fig. 3f) shows that after the contrast injection, the pixels with highest signal intensities (e.g., above 1500) are now almost all from the water pixels. This dramatic difference between the signal intensity profiles after the contrast agent injection violated the assumption in the pure-histogram based method and therefore resulted in a water and fat identification failure with an α -value of -1.0 . In comparison, the α -value by the spectrum based method was 0.25 and the water and fat identification was still correct.

Figure 4a) and b) show the water-only image and the corresponding fat-only image from a patient with a fatty liver. Without the geometric weighting factor, the spectrum-based water and fat identification method failed with an α -value of -0.04 . The pure-histogram based method worked correctly and yielded an α -value of 1. With the geometric factor weighting, the water and fat identification by the spectrum-based method became correct with an α value of 0.08. Although it is small compared to the average α value of all the images from different patients, it was consistently positive for all the slices for this patient and thus considered above fluctuations.

Discussion

Dixon techniques have become an appealing alternative for several clinical applications with the recent developments in phase correction algorithms and data acquisition strategies (4). As a result, several manufacturers of MR scanners have either introduced or are in the

process of introducing the Dixon techniques in their product offering. As a clinical imaging technique, reliable and automatic identification of water and fat images after they are separated is a basic and important requirement. Without correct identification, images can be mis-annotated. Furthermore, the actual water-only images may even be inadvertently discarded if a user selects to output and archive only one of the water-only and fat-only images. Correction of such an error would require a repeat in data acquisition or even a potential callback of the patient if injection of contrast agent were involved. The method proposed in this work helps avoid this type of mistakes and undesirable consequences. In comparison to a pure histogram based approach, the proposed method is based on the intrinsic spectral asymmetry between water and fat and therefore is expected to be much less sensitive to variations in the image intensity characteristics. The spectral asymmetry or the multi-peak feature of the fat spectrum have previously been explored for improved water and fat separation or tissue relaxation time measurement (16-18). However, most of the Dixon techniques have assumed a single-peak model for both water and fat and to the best of our knowledge, no previous work have used the spectral asymmetry for the purpose of identifying separated water and fat images – a task that has been considered impossible using phase information alone for symmetrically sampled Dixon images.

Our method is semi-empirical because we incorporated several refinements to the simple spectral asymmetry consideration. In our evaluation, these refinements are necessary and based on our observation that tissues with a mixture of water and fat (most notably fatty liver) are usually distributed towards the center of the images. While we cannot completely rule out a possibility where this assumption becomes invalid, we note that the final water and fat identification is dependent only on a statistically calculated parameter (i.e., A_{21} vs A_{12} comparison) and therefore is not expected to be sensitive to any small compromises to our assumptions (e.g., when a small number of pixels with water and fat co-existence are located towards the edge of the anatomy). While not included in our result, we further note that the proposed water and fat identification method was implemented as a product in the latest GE (GE Healthcare Technologies, Waukesha, WI) MR scanner platforms since May, 2008. As of this publication, we have not received any report of failure by the method from numerous customer installations.

Another note that should be made is that we implicitly assumed that water and fat separation has already been consistently achieved before the proposed water and fat identification method is applied. In our implementation, the water and fat separation is obtained after applying a region-growing based phase correction algorithm to remove the magnetic field inhomogeneity related phase errors (5,6). While the region-growing based phase correction has been shown reliable in clinical use (13,14), its result may be self-inconsistent when imaging some completely disconnected tissues (such as axial or coronal imaging of two legs). In such situations, identification of water and fat images becomes an ill-posed problem because the water-component of one leg may appear in the same image as the fat-component of the other leg. To overcome the dilemma, other types of phase correction (19) or improved region growing may be needed. We did not encounter the problem because we focused primarily on our target application of the abdomen and pelvic imaging. We recognize that a complete and full validation of our proposed method for imaging other anatomies may require more widespread testing on many different patients and on different scanners.

In summary, we proposed and demonstrated a semi-empirical but fully automated method for identification of water and fat images from a symmetrically sampled dual echo Dixon technique by exploiting the intrinsic asymmetry between the water and fat chemical shift spectra. The method further incorporated our empirical observation on the spatial distribution of fatty tissues and tissues with a mixture of water and fat. The method was successfully evaluated on a total of 131 three-dimensional actual patient datasets.

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Fig. 1.

Flowchart of the proposed water and fat image identification method based on the intrinsic asymmetry between water and fat chemical shift spectra.

Fig. 2. The α -distribution calculated from a total of 13496 total image pairs by the spectrum based method (a) and by the pure histogram based method (b).

Fig. 3.

(a) an example coronal water-only image acquired before the contrast injection. (b) The intensity histogram of the pre-contrast water-only image. (c) The intensity histogram of the corresponding pre-contrast fat-only image. (d) a post-contrast water-only image from the same location as in (a). (e) The intensity histogram of the post-contrast water-only image. (f) The intensity histogram of the corresponding post-contrast fat-only image. While the spectrum based image identification method was successful in both cases, the pure histogram based method failed due to the change in the intensity histogram of the water-only images before and after contrast injection.

Fig. 4.

The water-only (a) and the fat-only (b) image of a patient with fatty liver. The influence of a large number of pixels with appreciable amount of both water and fat is reduced with a geometric weighting factor, which leads to a correct α -value for image identification.