QUANTITIVE PROTON RESONANCE FREQUENCY IMAGING USING FAST MULTI-ECHO GRADIENT-ECHO

Wolfgang Stefan[1], Erol Yeniaras[1], Ken-Pin Hwang[2], Linda Chi[3], Ed Jackson[1], John D Hazle[1], and Roger Jason Stafford[1]

[1]*Imaging Physics, The University of Texas MD Anderson Cancer Center, Houston, Texas, United States,* [2]*Applied Science Laboratory, Healthcare Technologies, WI, Hosuton, Texas, United States,* [3]*Diagnostic & Radiology, The University of Texas MD Anderson Cancer Center, Houston, Texas, United States*

Introduction

Magnetic Resonance (MR) phase data can be used for soft tissue contrast as well as field shimming and artifact removal. One of the most prominent examples of using phase images as an additional contrast mechanism is susceptibility weighted imaging (SWI), which is useful in a wide variety of neuro-pathologies, e.g., traumatic brain injury, cerebral microhemorrhages, cerebrovascular disease, multiple sclerosis, intracranial hemorrhage, and tumors[1]. In order to make best use of phase data it is necessary to accurately separate the background phase (e.g., generated by local field inhomogeneities, air-tissue interfaces etc.) from the phase contributions of tissue magnetic susceptibility differences. Current heuristic background phase removal algorithms approximate the background field by polynomials or by a Fourier basis, while current non-heuristic methods model the background field by it's physical properties [2,3] Unfortunately, phase images contain wrapping artifacts and are contaminated by noise. However, the phase of a single image is dependent on the proton resonant frequency (PRF) of the spins in the image. Multiple fast echo (MFGRE) sequences are well suited to obtain accurate measurements of the PRF of the dominant tissue type on a pixel by pixel basis [4]. Herein, we introduce a semi-automatic algorithm for fast separation and unwrapping of the background field and local tissue-related PRF, which has the aforementioned useful information. The tissue related PRF is first recovered by solving a single peak ARMA [4] model and the background is removed by a novel background suppression technique. This background suppression is based on a compressed sensing type non-convex optimization, similar to [5], which finds sparse sharp gradients at tissue-tissue and tissue-air interfaces. In a second stage the PRF of an image without background field variations is constructed by fitting an image to the sharp gradients. The images can then be used to detect small PRF shifts for different tissue types. The restorations have the following properties: a) interfaces between homogeneous tissue regions are sparse, i.e. only relatively few pixels in the image can belong to interfaces, b) restorations are harmonic functions in homogeneous tissue and c) local phase changes between different tissue types are preserved. These three properties ensure physically meaningful restorations. Thus, our method has a heuristic component, by enforcing sparsity, and a non-heuristic component, by enforcing physical properties of the magnetic field. In other words the method extracts the brain structures from initial PRF map under the assumption that tissue-tissue interfaces are sparse, all other contributions to the initial PRF map are considered due to background.

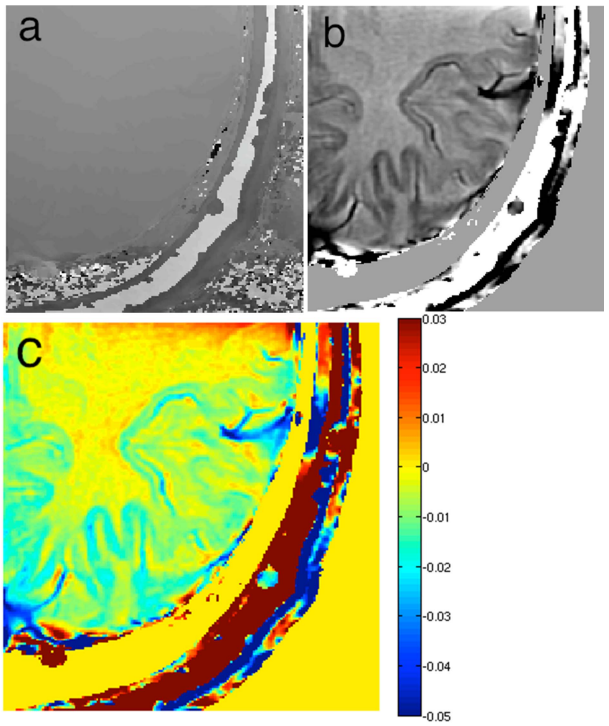

Fig 1: PRF map (a) before (WW 2.4ppm) and (b) after background removal (WW 0.08ppm); (c) false color PRF map in ppm. Anatomical structures are visible in (b) after removal of the background from (a) and re-windowing. PRF shifts of different tissue types can be read off (c)

Methodology

The MFGRE sequence is used to acquire gradient echo images from several echo times. Brain data was acquired using a 3T scanner (MR750; GE Healthcare Technologies, Waukesha, WI) from a healthy volunteer, using a MFGRE sequence with echo spacing = 3.392ms, number of echoes = 16, TE = 2.4 to 28.5 ms, TR = 2200 ms, flip = 60, FOV = 22cm, matrix = 320x256, slice thickness = 5mm, number of slices = 30. An initial PRF map is constructed by finding the dominant peak at each pixel using the method described in [4]. Next, the proposed background suppression technique is applied to remove the PRF shifts due to B_0 field in-homogeneities, i.e., sharp gradients are extracted from the PRF map in x- and y- direction using an l^1-minimization procedure similar to [5]. The l^1-minimization forces the sharp gradients to be limited to a few pixels. Therefore, sharp transitions between different tissue types are preserved while the gradient of the background, which is not sparse, is suppressed. Finally, an image is found by l^2-minimization which gradient fits the sharp gradients obtained by the l^1-minimization. Because the minimum satisfies the extreme value theorem, it follows that the restoration is an analytic function in regions without sharp gradients. Two parameters have to be chosen for the gradient extraction: the order (m) of the method and a regularization parameter (λ). If the background field is a polynomial of degree (m-1) without noise, then it is completely removed in the l^1-minimization process. For non-polynomial backgrounds the contribution up to order (m-1) is removed. We have found that choosing m=3 provides good results, where larger m may result in too much noise in the gradients and smaller m result in insufficiently suppressed background. In particular in the presence of noise, the regularization parameter (λ) is more influential but seem to be relatively robust for different applications. This parameter governs the smoothness of the background. We have found that a value of $\lambda=10^{-7}$ in brain results in good PRF maps. Jump discontinuities in the PRF maps due to aliasing are corrected by projecting the gradient to an interval defined by the echo-bandwidth.

Results and Conclusions

Figure 1(a) shows the PRF map resulting from the ARMA model [4] with a window width of 2.4ppm. The bright region in the picture results from the fatty tissue between skull and skin on the head. B_0 field in-homogeneities result in a shading effect that *masks* the underlying PRF changes due to different tissue types. Panel (b) is the result of the proposed background removal technique. The picture has a window width of 0.08ppm and is windowed such that the anatomical structure in the brain is visible. The bright fat content near the bone is outside the window and thus appears white. Panel (c) shows the same picture as (b) with false color-coding. The colors code the relative ppm-shift to the white matter in the top left of the image. A ppm-shift of about -0.015 ppm can be seen for gray matter and about -0.05 ppm for the veins in the image. Not visible in this image, but measurable, is the 2.4-3 ppm-shift of the fat tissue surrounding the skull. Limitations of the current implementation of the method can be seen in the very bright and dark regions near the brain boundary in (b). These are artifacts generated by the rapidly changing B0 field in this region. In this case the method could not distinguish between changes due to structure, or changes due to rapidly changing background. In future work we intend to incorporate a rough B0 field model into the method to avoid the problem.

We have developed a new background suppression technique that can be used to suppress the background in MR phase images and PRF measurements. In contrast to the most common approach of high pass filtering the phase to remove the background, our approach leaves the low frequency components of the tissue intact, which enables us to make quantitative measurements of the PRF.

References

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