Abstract—As demonstrated in previous work by Ziyan et al. [1], it is possible to estimate and remove respiration-induced signal fluctuations from multi-slice image-domain (magnitude and phase) fMRI data. However, this technique was limited to the analysis of over-sampled respiratory noise within a single imaged slice. This work presents a procedure to estimate the undersampled respiration waveform in multi-slice fMRI data when the slice acquisition rate is below the Nyquist rate. This technique is based upon the single-slice image-space (magnitude and phase) estimation and removal procedure developed of Ziyan et al. [1], and is presented as an alternative to the mathematically complex technique of Frank et al. [2] that uses k-space analysis to achieve similar ends.

Keywords - fMRI, physiologic noise, respiration, estimation

I. INTRODUCTION

Signal changes due to neuronal activity in functional MRI are typically small compared to the overall acquired signal. Therefore, it is essential to improve the signal-to-noise ratio for detection of neural involvement in particular activities. As hypothesized in [3] and demonstrated experimentally (e.g., [4]), one of the largest components of the fMRI noise is a signal fluctuation arising from respiration. Among the techniques proposed to remove respiration noise, one of the most attractive is the data-driven, k-space procedure of Frank et al. [2] that may be applied to multi-slice data, even when the TR is too long to achieve over-sampling of the respiration rate for a single slice. While this k-space technique is effective, it is computationally complex and requires greater involvement with the fMRI data than is common practice a clinical application. Therefore, we have developed an alternative technique that utilizes the readily-accessible magnitude and phase image data to estimate and remove the respiratory noise.

II. METHODOLOGY

A. Technique

The procedure to identify the respiratory noise in image-space data (magnitude and phase) follows.

1) Define a binary slice-mask to select slices from a volume that are to be used in development of a waveform estimate. This step excludes slices that contain a minimal number of brain voxels.

2) Generate an image-mask to preserve only those voxels meeting a user-defined threshold in all slices selected by the slice-mask.

3) Normalize the time-series of each voxel in the masked magnitude and phase images to a fixed mean (arbitrary for magnitude, zero for phase).

4) Compress range of phase values from (-\pi, \pi) to (\pi/8, 3\pi/8), and normalize the data to a fixed standard deviation. These efforts preserve linearity of temporal variations in phase angle after the next conversion.

5) Convert the magnitude and phase images (polar coordinates) to real and imaginary images (rectangular coordinates).

6) Average all voxels in each real and imaginary image.

7) Re-order the sums by time of acquisition to yield a single time-series for both the real and imaginary data. For slices excluded by the slice-mask, insert a zero into both time-courses.

8) Compute the FFT of each time-series.

9) Deconvolve the FFT of the periodic window effected by the slice-mask from the FFT's, yielding spectral estimates of respiratory waveforms for both real and imaginary data.

10) Band-pass filter to isolate respiration energy.

11) Obtain real and imaginary waveform time-series estimates using the inverse FFT of the spectral estimates. Removal of these final waveforms may be effected on a slice-by-slice basis using the amplitude-adaptive techniques developed by Ziyan et al. [1]. The resulting volumes may then be reconverted into polar co-ordinates and the magnitude images used for standard fMRI analysis.

B. Validation

The efficacy and accuracy of the proposed technique have been evaluated using data acquired both from a mechanical model of respiration and from human subjects. All fMRI data were acquired on a 1.5T imager (General Electric, Waukesha, WI) using a gradient-echo echo planar imaging sequence (TE = 40 ms).

Mechanical Model: 128 images of 9 slices (5mm thick; TR = 3 s) through a spherical water phantom were acquired on a 1.5T GE Signa while a mechanical model of respiration (Brosch et al. [5]) operated at rates of 6, 14 and 26 breaths per minute (bpm). The acquired data were analyzed using the procedure above applied to only the middle slice, to the complete volume and using a slice-mask that preserved only the central five slices.

Human Subject: 138 images of each of 20 slices (5 mm thick, 20 cm FOV, 64 x 64 matrix) were acquired using TR = 2 s. The subject’s respiration rate was measured to be approximately 25 bpm, too rapid for over-sampling.

III. RESULTS AND DISCUSSION

Mechanical Model: Respiration estimates generated from a single slice are shown at left in Fig. 1. Note that for each of the respiration rates (6, 14 and 26 bpm), the estimate...
obtained from a single slice is at 6 bpm. Estimates obtained using the proposed technique on the full volume are shown at right in Fig. 1. The correct estimate was obtained in each case. From the final estimate of the respiration waveform generated for 26 bpm, the estimated respiration waveform for one slice (generated by decimation) is shown at top in Fig. 2. The power spectrum of this time course (with respiration aliased at 6 bpm) is shown at bottom in Fig. 2.

Implementation of a slice-mask to limit the number of slices used to estimate the waveform is validated by the results in Fig. 3. The correct respiration rate estimate (26 bpm) was obtained using a slice-mask to limit analysis to the middle five of the nine slices.

**Human Subject:** Application to humans is demonstrated in Fig. 4. The use of all 20 slices in the time-series (and the resulting small image-mask) produces the spectrum shown at top. The slice-mask spectrum exhibits a peak at the respiration rate of 25 bpm, that is undersampled at TR = 2 s.

IV. CONCLUSION

We have successfully implemented an image-space based procedure for the estimation of under-sampled respiratory information in multi-slice fMRI data. Because no external monitoring is needed to identify this interference, this technique is applicable to clinical applications of fMRI.

REFERENCES


