Published in final edited form as:

J Magn Reson Imaging. 2015 August ; 42(2): 407–420. doi:10.1002/jmri.24785.

Free-Breathing Pediatric MRI with Nonrigid Motion Correction and Acceleration

Joseph Y. Cheng, PhD^{1,2}, Tao Zhang, PhD^{1,2}, Nichanan Ruangwattanapaisarn, MD³, Marcus T. Alley, PhD², Martin Uecker, PhD⁴, John M. Pauly, PhD¹, Michael Lustig, PhD⁴, and Shreyas S. Vasanawala, MD, PhD²

¹Magnetic Resonance Systems Research Laboratory, Department of Electrical Engineering, Stanford University, Stanford, California ²Department of Radiology, Stanford University, California

³Faculty of Medicine Ramathibodi Hospital, Mahidol University, Bangkok, Thailand ⁴Department of Electrical Engineering and Computer Sciences, University of California, Berkeley, California

Abstract

Purpose—To develop and assess motion correction techniques for high-resolution pediatric abdominal volumetric MR images acquired free breathing with high scan efficiency.

Materials and Methods—First, variable-density sampling and radial-like phase-encode ordering are incorporated into the 3D Cartesian acquisition. Second, intrinsic multi-channel Butterfly navigators are used to measure respiratory motion. Lastly, these estimates are applied for both motion-weighted data-consistency in a compressed sensing and parallel imaging reconstruction, and for nonrigid motion correction using a localized autofocusing framework.

With Institutional Review Board approval and informed consent/assent, studies were performed on 22 consecutive pediatric patients. Two radiologists independently scored the images for overall image quality, degree of motion artifacts, and sharpness of hepatic vessels and the diaphragm. The results are assessed using paired Wilcoxon test and weighted kappa coefficient for inter-observer agreements.

Results—The complete procedure yielded significantly better overall image quality (mean score of 4.7 out of 5) when compared to using no correction (mean score of 3.4, P value < 0.05) and to using motion-weighted accelerated imaging (mean score of 3.9, P value < 0.05). With an average scan time of 28 s, the proposed method resulted in comparable image quality to conventional prospective respiratory-triggered acquisitions with an average scan time of 91 s (mean score of 4.5).

Conclusion—With the proposed methods, diagnosable high-resolution abdominal volumetric scans can be obtained from free breathing data acquisitions.

Keywords

pediatric abdominal MRI; nonrigid motion; soft-gating; autofocus; parallel imaging; compressed sensing

INTRODUCTION

Magnetic resonance imaging (MRI) is a compelling choice for pediatric patients, as this population is highly susceptible to risks from ionizing radiation induced by alternative modalities such as computed-tomography and nuclear scintigraphy. Through recent developments, high resolution volumetric scans can be achieved in under a minute using accelerated imaging – more specifically, parallel imaging (1–3) and compressed sensing (4–6). The reduced duration allows for the acquisition of these scans over a single breath-hold. For uncooperative pediatric patients, the current clinical solution often involves intubating these patients with deep anesthesia and temporarily suspending their respiration during the scans. The setup and monitoring of the procedure are not only costly and complicated but also subject patients to risks. At sites where breath-holding cannot be performed and for patients with high risk profiles precluding such deep anesthesia, the quality and reliability of the MR images are limited. Prospective respiratory triggering/gating is an alternative solution that eliminates the need for breath-holds. However, approximately three-fold increase in scan time is typically required.

The purpose of this work is to develop a method for abdominal volumetric scans acquired completely free-breathing. For high scan efficiency, data are acquired continuously. Afterward, reconstruction schemes are used to compensate for respiratory motion. We investigate approaches to apply compressed sensing to motion correction (7–9). The structure and severity of image artifacts from motion depend on how the data are acquired and how the images are reconstructed. Thus, in order to effectively correct for motion while retaining the ability to accelerate, we propose a complete procedure that includes both data acquisition and image reconstruction methods.

For data acquisition, radial imaging (10–12) and radial-Cartesian hybrid imaging (13,14) exhibit advantageous motion properties while sampling in a variable-density manner. Therefore, we modify the 3D Cartesian acquisition to include both variable-density sampling and radial-like phase-encode ordering. We will refer to this approach as Variable-Density sampling and Radial view ordering (VDRad).

In image reconstruction, one common approach to correct for respiratory (or other repetitive type of) motion is to segment the k-space data into different respiratory states. This nonrigid motion can be corrected by exploiting the image correlations between these different states or by directly warping (15–18) the images into a single state. For broader clinical use, a simpler yet effective approach is explored. We first limit the adverse effects of heavily-corrupted data by weighting the data in our parallel imaging and compressed sensing reconstruction by the amount of motion that occurred (19–22). We will refer to this approach as “soft-gating” since it is a relaxation of retrospective gating (accept/reject). Finally, we approximate nonrigid motion as different local translations. This model is used

in a localized autofocusing technique to correct for nonrigid motion (23). Here, we incorporate soft-gating into the reconstruction to assist autofocusing by reducing motion corruption.

Our purpose is to achieve high quality images in free-breathing pediatric imaging through the combination of both data acquisition and image reconstruction strategies, and to assess the impact of these strategies on image quality for volumetric abdominal MRI scans.

MATERIALS AND METHODS

Data Acquisition: View-Ordering and Sampling with VDRad

The VDRad scheme aims to improve upon existing radial view-ordering techniques (24–28). It adds flexibility in setting the amount of variable density sampling that is desired. Also, it allows for arbitrary acceleration factors (both isotropic and anisotropic) to cater to different coil array configurations. The VDRad scheme aims to maintain a variable-density pseudo-random subsampling regardless if sets of temporally contiguous data are discarded (due to motion). We provide an overview of VDRad here. A detailed description of the implementation is provided in the Appendix. Software to generate the sampling is provided at the authors' website.

Each (k_y, k_z) -point on the Cartesian grid is referred to as a *view*. To facilitate the view-ordering construction, views are segmented according to k-space radius and grouped into *rings* (Fig. 1a). Views are acquired in groups referred to as *spokes*. Each spoke consists of one view from each ring (Fig. 1b). To control the variable density, the number of views per ring is varied. In this way, views from smaller ring groups are chosen more often than views in larger ring groups. The advantage in this approach is that the variable-density sampling pattern is maintained even if entire spokes are discarded. Variable-density sampling has been shown to work well for compressed sensing methods (4).

Spokes are acquired according to the golden angle (14,29). With this scheme, spokes acquired within an arbitrary time window will be (approximately) evenly distributed throughout k-space. Patient motion typically occurs smoothly in time; temporally adjacent spokes encounter a similar amount of motion. Thus, for each time window with data corruption from motion, the corrupted data samples are distributed throughout k-space. This effect is enhanced using a spiral twist in the spokes to further disperse the views within each spoke (Fig. 1b).

An example sampling mask generated from this scheme is illustrated on the left of Fig. 2c. A free-breathing acquisition reconstructed using conventional parallel imaging and compressed sensing (30) is shown adjacent to the sampling mask. Despite the presence of respiratory motion, there are no apparent motion ghosts.

Motion Measurement: Butterfly Navigators

In this work, we estimate motion from Butterfly navigators (23,31). These navigators are built into the prewinders of the Cartesian acquisition scheme and require very little overhead to the length of repetition time (TR). Butterfly navigators provide 3D translation motion

estimates for each coil (23,32) for every view. This enables both the estimation of the amount of corruption in each data point for soft-gating as well as the development of a motion model to correct for some nonrigid motion using autofocusing.

Accelerated Imaging with Soft-Gating

In its core, our reconstruction uses parallel imaging (1–3) and compressed sensing (4,30,33) to exploit the coil sensitivities and image transform sparsity for recovering both unacquired and corrupted k-space samples. For parallel imaging, we use the recently introduced ESPIRiT (30) approach – an auto-calibrating technique based on SPIRiT (33). In ESPIRiT, sensitivity maps are estimated through an eigenvalue decomposition of the data from a compact calibration region in k-space. These maps are used in a modified SENSE (2,30) reconstruction. When including sparsity constraints for compressed sensing, the reconstruction can be written as an unconstrained optimization problem:

$$\underset{m}{\operatorname{argmin}} \|D\mathcal{F}Sm - y\|_2^2 + \lambda \|\Psi m\|_1. \quad [1]$$

Here, m is the desired image(s), y is the acquired data, S is the ESPIRiT maps operator, $\mathcal{F}$ is a Fourier operator, and D is a k-space sampling operator selecting the acquired data. The first term in Eq. [1] is a data consistency term that minimizes the difference between the acquired data y and the reconstructed image m through the acquisition model. The second term enforces sparsity by minimizing the ℓ_1 -norm of the wavelet coefficients of m (4). The wavelet transform operator is represented by ψ . We solve the optimization in Eq. [1] using a fast iterative shrinkage-thresholding algorithm (FISTA) (34).

Patient motion during the scan will result in data corruption. The corrupted data are no longer consistent with the imaging model and may introduce image artifacts. To account for these inconsistencies, we use the Butterfly motion estimates to weight the data consistency term in Eq. [1] by the amount of motion that occurred. For free-breathing abdominal imaging, this corresponds to “soft-gating” the acquisition to nonrigid respiratory motion. Soft-gating is implemented by modifying Eq. [1] to

$$\underset{m}{\operatorname{argmin}} \|W(D\mathcal{F}Sm - y)\|_2^2 + \lambda \|\Psi m\|_1, \quad [2]$$

where W is a diagonal matrix containing the weights (19–22). The weights take a range of values between zero and one. Weights closer to unity imply that the corresponding data are assumed to be motion-free. Weights closer to zero mean that the corresponding data are corrupted, and therefore, the data consistency should incur very little penalty on the objective function. With the pseudo-random-like ordering of VDRad, the weighting is distributed non-uniformly throughout k-space. The resulting non-uniform k-space subsampling fits well with compressed sensing theory, which we use here to partially recover corrupted data.

A different weight $w[n]$ is computed and applied to the data consistency term for each view. The weighting is computed in the following way: For the i -th coil at the n -th TR, the Butterfly navigator provides a 3D translation motion estimate $\mathbf{d}_i[n] = (d_x[n], d_y[n], d_z[n])$.

The M motion estimates from M different channels are combined into $\bar{d}[n]$ using root mean square,

$$\bar{d}[n] = \sqrt{\frac{1}{M} \sum_{i=0}^{M-1} \|d_i[n]\|^2}. \quad [3]$$

The weighting $w[n]$ is determined from $\bar{d}[n]$ by computing

$$w[n] = \begin{cases} e^{-c_\alpha \{\bar{d}[n] - (c_{th} + c_k k_r^2[n])\}}, & \text{if } \bar{d}[n] > (c_{th} + c_k k_r^2[n]). \\ 1, & \text{otherwise} \end{cases} \quad [4]$$

The threshold is set by c_{th} . Motion less than c_{th} is assumed to be free from motion-corruption; motion greater than this threshold is exponentially weighted down. An additional term $c_k k_r^2[n]$ adjusts the threshold for each readout according to its artifact power (35), which is roughly proportional to the square of the distance from the center of k-space as $k_r^2[n] = k_y^2[n] + k_z^2[n]$. The weights calculated from Eqs. [3] and [4] are demonstrated in Fig. 2 for $c_{th} = 0.25$ pixels, $c_\alpha = 1$, and $c_k = 0$ with $k_r[n]$ in terms of pixels⁻¹. For our studies, we used $c_{th} = 0.25$ pixels, $c_\alpha = 1$, and $c_k = 4$, which were qualitatively determined to be effective based on empirical experiments.

Nonrigid Motion Correction through Localized Autofocusing

Soft gating has an inherent tradeoff between reducing data inconsistencies and increasing effective undersampling. To improve upon this tradeoff, we use motion correction to address residual artifacts from soft-gating. We build upon the previously proposed localized autofocusing framework (23). In this framework, nonrigid motion is approximated as simple localized linear translations. Butterfly navigators provide M different motion estimates from each element in a coil array. These are estimates of translations within the relatively restricted field of view (FOV) of each coil. A bank of M images is created where each image is corrected and reconstructed with a different motion estimate. The correction for one motion estimate is performed by applying the appropriate linear-phase correction in k-space. Each of these M images will have improved image quality in regions where the correction fits the actual motion, and reduced image quality elsewhere. A motion metric is applied locally for each image position to determine which correction yielded the best reconstruction (23). The metric we use in this work is localized gradient entropy (23). By minimizing this motion metric for each pixel, the final corrected image is pieced together in image space. The search space can be expanded by considering linear combinations or simple scalings (36) of these M motion measurements.

To incorporate autofocusing with the soft-gated parallel imaging and compressed sensing reconstruction, M reconstructions are performed, each corrected with a different motion path $d_i[n]$. Afterward, the localized gradient entropy metric is used to construct a single final image. A summary of the algorithm is described in Fig. 3.

Experiments

In Vivo Scan Setup—With Institutional Review Board approval and informed consent/assent, in vivo studies were performed on 22 consecutive pediatric patients, ranging from 2.2 to 10.7 years of age. These patients consisted of 13 females and 9 males. They were referred for abdominal MRI with different clinical indications that are specified in Table 1. The protocol included dynamic contrast-enhanced imaging performed with the patient freely breathing. Studies were performed on a GE MR750 3T scanner (Waukesha, WI, USA) using a 32-channel cardiac coil and a 3D spoiled gradient echo acquisition sequence. A flip angle of 15° , a readout bandwidth of ± 100 kHz, partial readout (0.6 of the full readout) to achieve minimum echo time (1.2–1.3 ms), and minimum TR (3.0–3.4 ms) were used for these studies. Motion was estimated using Butterfly navigators (23,32). For each TR, the navigator acquisition was 0.10–0.12 ms long and reached a maximum k-space radius of $0.4\text{--}0.6\text{ cm}^{-1}$. The acquisition of 3–4 temporal phases was designed using VDRad where each temporal phase had an acceleration of ~ 6 . In our reconstructions, data from the different temporal phases are combined into one phase. Fat-suppression was incorporated with a periodic spectral fat-inversion pulse (inversion time of 9.0 ms) with 24–27 views following each fat-inversion pulse. Data were acquired ~ 1.5 min after intravenous gadolinium-based contrast administration during the venous phases.

All pediatric patient studies were acquired completely free-breathing under light anesthesia. For comparison, a prospective respiratory-triggered/gated scan was performed immediately after the proposed scan using conventional respiratory bellows. These scans were acquired using a trigger point of 30% of maximum and an acceptance window of 30%. Table 1 describes ages, genders, specific contrast agent used, and other details about each study. After the data acquisition, motion was estimated from the navigators. Images were reconstructed using a combination of C/C++ and Matlab (Mathworks, Natick, MA, USA).

Image Evaluation—Reconstructed images were independently evaluated by two pediatric radiologists (S.S.V. with 9 years of experience and N.R. with 2 years of experience). The goal was to assess the improvement in diagnostic quality by including different motion-compensation components. To keep the analysis manageable, we consider the effects of sequentially adding different components to the reconstruction. Starting with the free-breathing continuous data acquisition using VDRad, conventional parallel imaging with compressed sensing (CS) was used to reconstruct the images. Afterward, CS was extended to reconstruct images using soft-gating (SG). Lastly, SG was extended to a combined soft-gated reconstruction with autofocusing framework (wAF). Respiratory-triggered/gated scans with conventional parallel imaging and compressed sensing (RT) were also included in the evaluation for comparison.

The reconstructions were assessed in the following features: (a) overall image quality, (b) degree of non-cardiac motion ghosts, and (c) the delineation of specific anatomical structures (including the hepatic artery/vein, diaphragm, and adrenal gland). Different reconstructions were independently evaluated in a blinded fashion using the scoring criteria described in Table 2.

A paired Wilcoxon test was used to test the null hypothesis that there was no significant difference between the different pairs of reconstructions. *P* value of less than 0.05 was considered statistically significant. Weighted kappa coefficient was used to assess the inter-observer agreement with the following scale: almost perfect (0.8–1.0), substantial (0.6–0.8), moderate (0.4–0.6), fair (0.2–0.4), slight (0.0–0.2), and poor (<0.0).

RESULTS

Example cases are shown in Figs. 4 and 5. For completeness, autofocusing without soft-gating is included in Fig. 4 as AF. When compared to AF, wAF has sharper hepatic arteries and less noise. A summary of the image assessment is shown in Fig. 6. Additionally, the mean scores and the results from the paired Wilcoxon test are shown in Table 3. Based on the weighted kappa coefficients (Table 4), the two readers had at moderate to substantial for the majority of the image assessments.

For the overall image quality, SG and wAF were all diagnostically acceptable for both readers (Fig. 6a). One outlier case for RT had limited diagnostic quality. This was the result of the inability to obtain a steady respiratory bellows signal from the small patient. This resulted in poor respiratory triggering/gating (Fig. 5b). Comparing the different reconstructions, overall image quality of SG was statistically superior to simple CS. Also, wAF was statistically superior to both CS and SG.

The degree of coherent non-cardiac motion ghosts was acceptable for the majority of the cases with mean scores of 4.1 and higher (Table 3) for all reconstructions. The outlier RT case (Fig. 6b) had limited diagnostic quality in terms of motion ghosts (Fig. 5b).

Over 60% of the cases for CS, and SG and nearly 50% for RT had limited to nondiagnostic quality when looking at the hepatic artery, whereas less than 50% of the wAF cases had limited to nondiagnostic quality of the hepatic artery (Fig. 6c). In Fig. 4, SG recovered the hepatic arteries that were not delineated in CS. With wAF, the delineation of the hepatic arteries was further enhanced. In Fig. 5c, wAF was able to recover the bifurcation of the hepatic arteries. For both readers, wAF was statistically superior to CS, SG, and RT. For RT, the poor delineation of the hepatic arteries was because the RT scans were acquired after the free-breathing continuous scans. By then, the contrast enhancement of the adjacent veins obscure delineation of the hepatic artery (Figs. 4 and 5c).

Majority of the RT and wAF cases resulted in acceptable diagnosable depiction of the hepatic vein with 90% cases acceptable for RT and 95% acceptable for wAF (Fig. 6d). CS had only 35% and SG had 60% of the cases that were acceptable for diagnosing the hepatic vein. With a statistically significant difference, the hepatic vein appeared better in the wAF cases when compared to CS and SG. Similarly, with statistical significance, RT had better depiction of the hepatic vein when compared to CS and SG. There was no clear statistical difference between RT and wAF. An example case in Fig. 5a shows clear delineation of the first and second order branches of the hepatic vein in both wAF and RT.

For the delineation of the diaphragm, 70% of the RT cases, nearly 20% of the CS cases, 35% of the SG cases, and 55% of the wAF cases were diagnostically acceptable (Fig. 6e).

For CS, the readers had only slight agreement (Table 4). Without any motion correction elements in the CS image reconstruction, this structure with considerable respiratory motion was more difficult to interpret objectively. The readers were more in agreement (moderate to substantial) when motion compensation element was added in SG, wAF, and RT. Nevertheless, the two readers determined that both wAF and RT were statistically superior to CS. RT and wAF were also superior to SG with statistical significance. In Fig. 4, an example is shown where the diaphragm structure can be seen; the diaphragm appeared sharpest in wAF and RT.

All cases for wAF resulted in acceptable diagnostic quality of the adrenal gland. A few outlier RT cases had limited diagnosability of the adrenal gland. Nearly 80% of CS and 85% of SG were acceptable (Fig. 6f). wAF was statistically superior compared to CS and SG. Similarly, RT was statistically superior compared to CS and SG.

DISCUSSION

Starting with a basic free-breathing acquisition, much effort was made to reduce data corruption from motion to achieve high quality MRI scans. With VDRad, the data acquisition scheme was designed and tuned to reduce severe ghosting artifacts typically seen in Cartesian scans. Additionally, steps were taken to ensure a sampling pattern suitable for parallel imaging and compressed sensing. The features of this pattern were maintained despite corruption from motion. Parallel imaging enhanced with compressed sensing enabled the flexibility to discard corrupt data samples while still being able to reconstruct the scans (7–9). Soft-gating was incorporated as an effective scheme to reduce the impact of overly corrupt samples in our iterative reconstruction. Lastly, autofocusing using motion estimates from a high-density coil array was used to correct for residual motion blurring.

In many cases, the degree of motion in pediatric patients was minimal, and the VDRad acquisition by itself was sufficient to reduce most image artifacts as noted by CS cases with acceptable diagnostic image quality. Furthermore, nearly all reconstructions resulted in acceptable diagnostic quality in terms of coherent non-cardiac motion. This implies that the VDRad scheme is effective in minimizing motion artifacts that may impair the diagnostic quality of the images.

However, VDRad alone was insufficient in reliably recovering anatomical structures corrupted by respiratory motion. The effects of data acquisition and image reconstruction strategies are inherently coupled. VDRad with soft-gating reduces coherent global artifacts. As a result, the chance of erroneously sharpening these global artifacts is minimized. Additionally, residual global artifacts that we want autofocusing to ignore are reduced. When one image region is focused, we want to minimize the introduction of additional artifacts generated from an unfocused region into the focused region. This effect was observed with a decrease in apparent noise when comparing wAF to the non-soft-gated version.

Theoretically, if the same scan durations are prescribed, SG should yield similar results to conventional RT. The lower mean scores of SG compared to RT in our evaluation can be

mainly attributed to insufficient motion-free data collected for SG; a shorter scan (average 28 s) was used for SG compared to RT (average 91 s). With the addition of autofocusing, there were no significant differences in the mean scores between wAF and RT. In other words, autofocusing enables a scan time reduction by accepting and correcting the corrupted data. It may be possible to further reduce the scan time while maintaining high spatial resolution. However, further investigation must be performed to determine exactly how much acceleration can be gained from the motion compensation techniques.

The presented motion compensation steps can be applied individually, as a combination of a few, or more ideally, as a combination of all steps. We observed sequential improvements when steps were sequentially introduced. SG alone was statistically superior to CS in terms of overall image quality, but the comparison between the different anatomical structures was less conclusive. With all reconstruction steps applied, wAF yielded statistically superior results compared to conventional CS and SG for both overall image quality and the delineation of structures. Thus, for reliability, we suggest including all motion compensation components for pediatric imaging.

When including all components, one concern is the duration of the entire reconstruction. With wAF, the bulk of the computation is from applying M different motion candidates for M different volumes. Fortunately, 3D Cartesian reconstruction is highly parallelizable: the reconstruction can be performed slice-by-slice in the hybrid (x, k_y, k_z) -space. As a result, each x -slice for each motion candidate can be simultaneously reconstructed on an independent computing node. In our current limited setup, we are already approaching clinically realizable times. The reconstruction of one motion candidate was completed in ~ 0.5 min on a 12-CPU-core machine. The entire wAF method (for $M = 32$) was completed in less than 20 min. The reconstruction time can be further reduced with additional parallel computing nodes.

We have developed and evaluated these motion compensation techniques for contrast-enhanced T1-weighted volumetric scans. The presented work can be translated to other sequences in a typical pediatric abdominal exam, such as T2-weighted imaging and diffusion-weighted imaging (DWI). On the other hand, 2D variants of these techniques, including T2-weighted single shot fast spin echo and single shot echo planar DWI, are already robust to motion.

The sequence setup was matched as best as possible across the patient population. Our study focused on volumetric scans acquired in the coronal orientation. In this orientation, motion artifacts propagate most noticeably in the axial directions. An advantageous feature of VDRad is that these propagated artifacts are incoherent, and this feature is independent of the scan orientation prescribed. Thus, we hypothesize that wAF with VDRad can also be effective in achieving high image quality for free-breathing scans in other orientations.

The focus was to correct for nonrigid respiratory motion that is periodic in nature. The proposed techniques can be applied for cardiac motion and more general motions. These methods can also be applied for certain adult patients who have difficulty performing breath-

holds. Adult patients typically have a wider range in respiratory motion; more data may be needed for an acceptable image reconstruction.

Another unexplored element is the impact of the receiver coil hardware. First, different acceleration factors are supported by different configurations of the coil receivers. Since soft-gating is essentially a subsampling operation, different levels of soft-gating are also supported by different configurations of the coil receivers. Thus, a longer scan may be required for a coil array with fewer and larger receiver elements. Second, the ability to capture local motion using Butterfly navigators is dependent on the density and channel count of the receiver coil array. The performance of wAF over SG depends on the localization of these motion estimates. Fortunately, wAF can also be accomplished with simple scalings of motion estimates (36).

We assessed the impact of our motion correction techniques on image quality. Anatomical structures (hepatic vessels, diaphragm, and adrenal gland) were determined to be better delineated in wAF; this finding does suggest the ability to better diagnose diseases related to these structures. However, we did not in this study assess whether or not the sensitivity and specificity for diagnosis of various pathologies improve with the use of the presented method.

Another limitation to the image evaluation was the absence of a reference standard. An alternative is performing breath-holds. However, breath-holds in uncooperative patients require intubation; this procedure is not practical given its risks and costs. Under this constraint, RT provided a means for a rough comparison. For imaging pediatric patients, obtaining a sufficient respiratory signal using respiratory bellows can be quite challenging given the smaller patient size. For instance, both readers considered one RT case as nondiagnostic for overall image quality, motion ghosts, hepatic artery, hepatic vein, and diaphragm. Additionally, due to contrast timing limitation, the RT scans innately had poor delineation of the hepatic arteries. Furthermore, the evaluation could not be truly blinded because of the different contrast from these scans. Nevertheless, for all other cases and other parameters, RT provided a sufficient comparison. The absence of a reference standard for pediatric imaging emphasizes a need for a more effective imaging approach.

A limitation to the clinical evaluation was the small number of patients. A primary objective of this work was to develop a completely free-breathing method. Therefore, only a small patient population was recruited to demonstrate the feasibility of the proposed method. Even after applying the Benjamini-Hochberg correction for multiple comparisons, the results for statistical significance were still the same; this furthers our confidence in our results.

In conclusion, a comprehensive solution to enable free-breathing exams for pediatric patients is presented. Both data acquisition and image reconstruction methods were used to effectively correct for motion corruption. We proposed the use of VDRad to continuously sample/order 3D Cartesian data. We also incorporated autofocusing with soft-gating to retrospectively reduce and correct for image artifacts from nonrigid motion. By combining these methods, we demonstrated statistically significant improvements in image quality for pediatric abdominal MRI studies with reduced depth of anesthesia.

Acknowledgments

Grant Support: Child Health Research Institute, Lucile Packard Foundation for Children's Health, Stanford CTSA (UL1 TR001085), NIH grants R01-EB009690 & P41-EB015891, AHA 12BGIA9660006, Sloan Research Fellowship, and GE Healthcare.

APPENDIX: IMPLEMENTATION FOR VDRAD

The design is illustrated in Fig. 1. Matlab demonstration¹ is available for download at <http://mrsrl.stanford.edu/~jycheng/software.html>.

The proposed technique depends on a number of user-defined parameters:

- L_r = number of views in one spoke (also number of rings)
- (R_y, R_z) = acceleration factors in y and z (both ≥ 1)
- N_{total} = number of views for fully sampled acquisition
- N_{calib} = number of views for the calibration region (used for parallel imaging)

A typical value of L_r that we use is around 27. The value of N_{total} is determined by the imaging resolution, FOV, and if k-space corners are desired or not. In our experiments, we set the diameter of the calibration region to be 24-views wide yielding $N_{calib} \approx 450$. From these user-defined parameters, the desired number of spokes (P_{spokes}) and the number of rings that make up the calibration region (L_{calib}) can be calculated:

$$P_{spokes} = \left\lceil \frac{N_{total}}{R_y R_z L_r} \right\rceil, \quad [A1]$$

$$L_{calib} = \left\lceil \frac{N_{calib}}{P_{spokes}} \right\rceil. \quad [A2]$$

Because the method is applied in discrete space, P_{spokes} and L_{calib} must be integers. The floor function is used in Eq. [A1] to first construct the sampling/ordering structure. More spokes are added later to achieve the desired acceleration. The ceiling function is applied in Eq. [A2] to ensure that sufficient samples are acquired for the calibration region. Note, the value of N_{total}/N_{calib} cannot achieve less than the desired acceleration, or

$$\frac{N_{total}}{N_{calib}} \geq R_y R_z. \quad [A3]$$

Next, the number of views per ring is determined. The first L_{calib} rings contain P_{spokes} number of views. For all other rings, a variable increase in acceleration can be added with rate v . Inspired by the variable density in radial imaging, we set $v = 1$ in our setup. This corresponds to a linearly increasing acceleration, or in other words, a linear increase in number of views. We determine the number of views for each ring i as $N_{views}[i]$:

¹VDRad_MATLAB_v0.1.zip (SHA-1: 0eae5fa2f99780e6ab413fd5e40e08a123920430)

$$N_{views}[i] = \begin{cases} P_{spokes} & \text{if } 0 \leq i < L_{calib} \\ R_g(i - L_{calib} + 1)^v + P_{spokes} & \text{if } L_{calib} \leq i < L_r \end{cases} \quad [A4]$$

Given N_{total} views, we have the following constraint:

$$N_{total} = \sum_{i=0}^{L_r-1} N_{views}[i]. \quad [A5]$$

From Eqs. [A4] and [A5], an expression for R_g is derived as

$$R_g = \frac{N_{total} - P_{spokes}L_r}{\sum_{i=1}^{L_r-L_{calib}} i^v}. \quad [A6]$$

Using R_g defined by Eq. [A6], the values of $N_{views}[i]$ for $0 \leq i < L_r - 1$ are determined by evaluating Eq. [A4]. The last ring size is calculated separately to satisfy the constraint in Eq. [A5]:

$$N_{views}[L_r - 1] = N_{total} - \sum_{i=0}^{L_r-2} N_{views}[i]. \quad [A7]$$

After determining the number of views in each ring, the actual view-ordering and sampling is constructed. Descriptions for each step of the algorithm are as follows:

1. *Setup*:
 - a. For each (k_y, k_z) -view to collect, determine the corresponding k-space radius k_r and k-space angle k_θ
 - b. Order the samples first by k_r and then by k_θ
 - c. Divide the ordered views into L_r rings where the number of consecutive views in each ring is given by $N_{views}[i]$.
2. *Ordering each ring*: Using k_θ sample and order each view according to the golden angle (29): $360^\circ/\psi \approx 222.5^\circ \Rightarrow 137.5^\circ$ where $\psi = (1 + \sqrt{5})/2$.
3. *Build spokes*: Build spoke j by selecting the j -th sample in each ring.
4. *Final re-ordering*: For each spoke, the samples are re-ordered in a center-out fashion to consider fat-inversion blocks and other techniques that introduce signal modulations (37). Alternatively, the samples can be re-ordered for optimal smoothness to minimize eddy currents (38).

The value of L_r may impact the scheme's effectiveness against motion corruption. If the time to acquire L_r views aligns perfectly with the duration of one phase in the respiratory cycle, data inconsistencies from respiration will not be distributed throughout k-space. In the worst case, motion corruption is greatest at the start of each radial spoke. As a result, corrupt samples become clustered around the center of k-space. To avoid this situation, we reduce $TR \times L_r$ to be sufficiently smaller ($TR \times L_r$ on the order of 0.1 s) than the duration of the

respiratory phase (2–4 s for pediatric patients). Another possible solution is to modify the ordering of the views from spoke to spoke.

In our experiments, we defined k_r and k_θ as

$$k_r(k_y, k_z) = \sqrt{(\alpha k_y)^2 + k_z^2} \quad [\text{A8}]$$

$$k_\theta(k_y, k_z) = \arg\{(\alpha k_y + i k_z) \times e^{i2\pi\beta k_r(k_y, k_z)}\}. \quad [\text{A9}]$$

Constant α in Eq. [A8] was defined as $\alpha = R_y/R_z$, warping each ring to account for anisotropic acceleration factors. This provided flexibility in the degree and anisotropy of the acceleration. Constant β in Eq. [A9] incorporated a spiral twist to each radial spoke to avoid coherent streaking artifacts associated with undersampling using conventional radial sampling patterns. Lastly, fat-suppression was used to minimize the impact of motion artifacts from the high fat signal. Fat-suppression was achieved by playing intermittent fat-inversion pulses before collecting a spoke of views ordered in a center-out fashion (37). The value of L_r was dictated by the more limiting constraint: either by the (a) number of views that can be acquired given a specific fat-inversion time or (b) the requirement to have $\text{TR} \times L_r$ much smaller than the duration of the respiratory phase.

REFERENCES

1. Sodickson DK, Manning WJ. Simultaneous acquisition of spatial harmonics (SMASH): fast imaging with radiofrequency coil arrays. *Magn Reson Med.* 1997; 38:591–603. [PubMed: 9324327]
2. Pruessmann KP, Weiger M, Scheidegger MB, Boesiger P. SENSE: sensitivity encoding for fast MRI. *Magn Reson Med.* 1999; 42:952–962. [PubMed: 10542355]
3. Griswold MA, Jakob PM, Heidemann RM, et al. Generalized autocalibrating partially parallel acquisitions (GRAPPA). *Magn Reson Med.* 2002; 47:1202–1210. [PubMed: 12111967]
4. Lustig M, Donoho D, Pauly JM. Sparse MRI: The application of compressed sensing for rapid MR imaging. *Magn Reson Med.* 2007; 58:1182–1195. [PubMed: 17969013]
5. Vasanawala SS, Alley MT, Hargreaves BA, Barth RA, Pauly JM, Lustig M. Improved pediatric MR imaging with compressed sensing. *Radiology.* 2010; 256:607–616. [PubMed: 20529991]
6. Zhang T, Chowdhury S, Lustig M, et al. Clinical performance of contrast enhanced abdominal pediatric MRI with fast combined parallel imaging compressed sensing reconstruction. *J Magn Reson Imaging.* 2014; 40:13–25. [PubMed: 24127123]
7. Bydder M, Larkman DJ, Hajnal JV. Detection and elimination of motion artifacts by regeneration of k-space. *Magn Reson Med.* 2002; 47:677–686. [PubMed: 11948728]
8. Barral, J.; Nishimura, D. Compressed sensing for motion artifact reduction; Proceedings of the 17th Annual Meeting of ISMRM; Honolulu, Hawai'i, USA. 2009. (abstract 4593)
9. Moghari MH, Akçakaya M, O'Connor A, et al. Compressed-sensing motion compensation (CosMo): a joint prospective-retrospective respiratory navigator for coronary MRI. *Magn Reson Med.* 2011; 66:1674–1681. [PubMed: 21671266]
10. Glover GH, Pauly JM. Projection reconstruction techniques for reduction of motion effects in MRI. *Magn Reson Med.* 1992; 28:275–289. [PubMed: 1461126]
11. Barger AV, Block WF, Toropov Y, Grist TM, Mistretta CA. Time-resolved contrast-enhanced imaging with isotropic resolution and broad coverage using an undersampled 3D projection trajectory. *Magn Reson Med.* 2002; 48:297–305. [PubMed: 12210938]

12. Chandarana H, Feng L, Block TK, et al. Free-breathing contrast-enhanced multiphase MRI of the liver using a combination of compressed sensing, parallel imaging, and golden-angle radial sampling. *Invest Radiol*. 2013; 48:10–16. [PubMed: 23192165]
13. Huang Y, Gurr D, Wright GA. Three-dimensional reconstruction of limited-view projections for contrast-enhanced magnetic resonance angiography at high temporal and spatial resolution. *Magn Reson Med*. 2006; 55:68–74. [PubMed: 16270330]
14. Prieto C, Uribe S, Razavi R, Atkinson D, Schaeffter T. 3D undersampled golden-radial phase encoding for DCE-MRA using inherently regularized iterative SENSE. *Magn Reson Med*. 2010; 64:514–526. [PubMed: 20665795]
15. Odille F, Vuissoz P-A, Marie P-Y, Felblinger J. Generalized reconstruction by inversion of coupled systems (GRICS) applied to free-breathing MRI. *Magn Reson Med*. 2008; 60:146–157. [PubMed: 18581355]
16. Buerger C, Schaeffter T, King AP. Hierarchical adaptive local affine registration for fast and robust respiratory motion estimation. *Medical Image Analysis*. 2011; 15:551–564. [PubMed: 21454119]
17. Schmidt JFM, Buehrer M, Boesiger P, Kozerke S. Nonrigid retrospective respiratory motion correction in whole-heart coronary MRA. *Magn Reson Med*. 2011; 66:1541–1549. [PubMed: 21604297]
18. Batchelor PG, Atkinson D, Irrazaval P, Hill DLG, Hajnal J, Larkman D. Matrix description of general motion correction applied to multishot images. *Magn Reson Med*. 2005; 54:1273–1280. [PubMed: 16155887]
19. Cheng, JY.; Uecker, M.; Alley, MT.; Vasanawala, SS.; Pauly, JM.; Lustig, M. Free-breathing pediatric imaging with nonrigid motion correction and parallel imaging; Proceedings of the 21st Annual Meeting of ISMRM; Salt Lake City, Utah, USA. 2013. (abstract 312)
20. Fang, S.; Ying, K. K-Space weighted multi-channel regularization for motion correction in multi-shot DWI; Proceedings of the 16th Annual Meeting of ISMRM, Toronto, Ontario; Canada. 2008. (abstract 1805)
21. Johnson KM, Block WF, Reeder SB, Samsonov A. Improved least squares MR image reconstruction using estimates of k-space data consistency. *Magn Reson Med*. 2012; 67:1600–1608. [PubMed: 22135155]
22. Forman C, Piccini D, Grimm R, Hutter J, Hornegger J, Zenge MO. Reduction of respiratory motion artifacts for free-breathing whole-heart coronary MRA by weighted iterative reconstruction. *Magn Reson Med*. 2014 in press.
23. Cheng JY, Alley MT, Cunningham CH, Vasanawala SS, Pauly JM, Lustig M. Nonrigid motion correction in 3D using autofocusing with localized linear translations. *Magn Reson Med*. 2012; 68:1785–1797. [PubMed: 22307933]
24. Madhuranthakam AJ, Hu HH, Barger AV, et al. Undersampled elliptical centric view-order for improved spatial resolution in contrast-enhanced MR angiography. *Magn Reson Med*. 2006; 55:50–58. [PubMed: 16315207]
25. Haider CR, Hu HH, Campeau NG, Huston J, Riederer SJ. 3D high temporal and spatial resolution contrast-enhanced MR angiography of the whole brain. *Magn Reson Med*. 2008; 60:749–760. [PubMed: 18727101]
26. Du J. Contrast-enhanced MR angiography using time resolved interleaved projection sampling with three-dimensional Cartesian phase and slice encoding (TRIPPS). *Magn Reson Med*. 2009; 61:918–924. [PubMed: 19195019]
27. Doneva, M.; Stehning, C.; Nehrke, K.; Börnert, P. Improving scan efficiency of respiratory gated imaging using compressed sensing with 3D Cartesian golden angle sampling; Proceedings of the 19th Annual Meeting of ISMRM, Montréal, Québec; Canada. 2011. (abstract 3057)
28. Henningsson M, Prieto C, Chiribiri A, Vaillant G, Razavi R, Botnar RM. Whole-heart coronary MRA with 3D affine motion correction using 3D image-based navigation. *Magn Reson Med*. 2014; 71:173–81. [PubMed: 23400902]
29. Winkelman S, Schaeffter T, Koehler T, Eggers H, Doessel O. An optimal radial profile order based on the Golden Ratio for time-resolved MRI. *IEEE Trans Med Imaging*. 2007; 26:68–76. [PubMed: 17243585]

30. Uecker M, Lai P, Murphy MJ, et al. ESPIRiT-an eigenvalue approach to autocalibrating parallel MRI: Where SENSE meets GRAPPA. *Magn Reson Med*. 2014; 71:990–1001. [PubMed: 23649942]
31. Lustig, M.; Cunningham, CH.; Daniyalzade, E.; Pauly, JM. Butterfly: a self navigating Cartesian trajectory; Proceedings of the Joint Annual Meeting ISMRM-ESMRMB; Berlin, Germany. 2007. (abstract 865)
32. Cunningham, C.; Lustig, M.; Pauly, J. Self navigating cartesian trajectory. US Patent. 7,692,423. 2010.
33. Lustig M, Pauly JM. SPIRiT: Iterative self-consistent parallel imaging reconstruction from arbitrary k-space. *Magn Reson Med*. 2010; 64:457–471. [PubMed: 20665790]
34. Beck A, Teboulle M. A fast iterative shrinkage-thresholding algorithm for linear inverse problems. *SIAM J Imaging Sci*. 2009; 2:183–202.
35. Weiger M, Börnert P, Proksa R, Schäffter T, Haase A. Motion-adapted gating based on k-space weighting for reduction of respiratory motion artifacts. *Magn Reson Med*. 1997; 38:322–333. [PubMed: 9256114]
36. Ingle RR, Wu HH, Addy NO, et al. Nonrigid autofocus motion correction for coronary MR angiography with a 3D cones trajectory. *Magn Reson Med*. 2014; 72:347–61. [PubMed: 24006292]
37. Busse RF, Brau ACS, Vu A, et al. Effects of refocusing flip angle modulation and view ordering in 3D fast spin echo. *Magn Reson Med*. 2008; 60:640–649. [PubMed: 18727082]
38. Jung BA, Hennig J, Scheffler K. Single-breathhold 3D–trueFISP cine cardiac imaging. *Magn Reson Med*. 2002; 48:921–925. [PubMed: 12418009]
39. Huang F, Vijayakumar S, Li Y, Hertel S, Duensing GR. A software channel compression technique for faster reconstruction with many channels. *Magn Reson Imaging*. 2008; 26:133–141. [PubMed: 17573223]
40. Zhang T, Pauly JM, Vasanawala SS, Lustig M. Coil compression for accelerated imaging with Cartesian sampling. *Magn Reson Med*. 2013; 69:571–582. [PubMed: 22488589]

Figure 1.

Variable-density sampling and radial view-ordering method overview. **a:** (k_y, k_z) -views divided into concentric rings where each ring has a different number of samples. **b:** Resulting sampling and view-ordering – views are colored according to the corresponding ring; the dark points are sampled after the calibration region is sufficiently covered. Each spoke is acquired according to the golden-ratio angle; this ordering is illustrated by the number next to each spoke. This method is applied to 3D Cartesian imaging – sampling on a Cartesian grid in the (k_y, k_z) -plane and a full readout in the k_x direction. Since rings closer to the center have fewer views, these rings are fully acquired more rapidly compared to the outer rings. This method generates the variable-density sampling.

Figure 2.

Soft-gated accelerated imaging using weights derived from the motion measurement. **a:** Magnitude translations where each color represents a measurement from a different channel in a coil array, the dark blue line corresponds to the root mean square of all measurements, and the solid yellow denotes the threshold at 0.25 pixels (px). **b:** Computed weights w from the root-mean-square motion measurement. **c:** Image reconstructions from a VDRad scan of a 5.7-year-old male (#5 of Table 1) using no weights (conventional parallel imaging with compressed sensing) and using weights (soft-gated). The sampling mask and the weighted sampling mask are displayed adjacent to the reconstructed images. By incorporating motion-based weights into the parallel imaging reconstruction, the data acquisition is soft-gated and an improvement to the image quality can be appreciated: the liver dome is sharpened (*yellow dashed arrow*) and a branch hepatic vein is recovered (*black arrow*).

Figure 3.

Nonrigid motion correction using localized autofocusing. **a:** Overview of the autofocusing framework – select steps are labeled here and described in more detail in **(b)** and **(c)**. **b:** Two-dimensional example of the Butterfly trajectory used to measure M motion path (d_1 , d_2 , ..., d_M) from an M -channel coil-array. **c:** For each motion measurement candidate, simple linear motion correction applied to all the multi-channel k-space data and a weighted parallel imaging (PI) and compressed sensing (CS) algorithm used to reconstruct the corrected image. For each pixel, the final image in **(a)** is constructed by selecting the reconstruction

that was corrected using the motion measurement that best minimizes the motion metric. To reduce the computation load, a coil-compression algorithm (39,40) can be applied to the raw k-space data to first compress the M -channels to M_v -channels of data. Coil compression is not performed on the navigator data to maintain the localization of M motion paths from M physical coils.

Author Manuscript

Author Manuscript

Author Manuscript

Author Manuscript

Figure 4.

Comparison of different image reconstructions with 5-slice maximum-intensity-projection of a 4.8-year-old male (#10 in Table 1). **CS:** Conventional parallel imaging with compressed sensing. **SG:** Soft-gated reconstruction. **AF:** Autofocusing with conventional parallel imaging with compressed sensing. **wAF:** Soft-gated AF. **RT:** Prospective respiratory triggered/gated acquisition. By applying either SG or AF, the hepatic arteries are recovered (*yellow dashes arrows*). Better delineation of these arteries can be appreciated in wAF. The diaphragm is also sharpened using wAF (*outlined triangle*). The results from wAF are comparable to RT.

Figure 5.

Example comparisons for the image assessment of anatomical structures. **a:** 11-slice maximum-intensity-projection of a 4.6-year-old female (#2 of Table 1). **b:** 1.6-year-old female (#6 of Table 1). **c:** 4.4-year-old female (#7 of Table 1). In **(a)**, the recovery of the first (yellow dashed arrow) and second order (outlined triangle) hepatic veins can be appreciated in SG and more so in wAF. For this case, wAF achieved similar quality when compared with RT. In **(b)**, RT resulted in poor image quality due to the inability to obtain a stable respiratory signal as demonstrated by the blurring of the hepatic veins (white arrow). In **(c)**, wAF recovered the bifurcation of the hepatic artery (yellow arrow) which was lost in both CS and SG.

Figure 6.

Image assessment results for conventional parallel imaging with compressed sensing (CS), soft-gating (SG), soft-gated autofocusing (wAF), and respiratory triggered (RT) as evaluated by two readers independently. **a:** Overall image quality. **b:** Degree of coherent non-cardiac motion ghosts. **c:** Hepatic artery. **d:** Hepatic vein. **e:** Sharpness of diaphragm. **f:** Adrenal gland. Each color bar represents the percentage of cases with the same score. For each reconstruction, the results of the two readers are placed side by side.

Table 1

Scan summary with acquisition times and clinical indications.

	Age [yrs]	Sex	S/I motion [mm]	Resolution [mm]	FOV [cm]	Scan time [s]			Contrast	Clinical indication
						FB*	RT*			
1	9.8	F	6.7	(1.2, 1.1, 2.6)	(38.0, 32.2, 20.8)	31.9	105.7		Multihance	Abdominal pain
2	4.6	F	4.3	(0.9, 1.2, 2.0)	(28.0, 22.4, 16.0)	41.0	103.5		Multihance	Wilms' post nephrectomy
3	2.1	F	4.8	(0.8, 1.2, 2.0)	(26.0, 18.2, 16.0)	23.4	80.2		Gadavist	Left renal lesion
4	3.9	F	4.5	(0.9, 1.3, 2.0)	(30.0, 24.0, 16.0)	40.1	102.6		Gadavist	Abdominal mass
5	5.7	M	10.7	(0.9, 1.3, 2.0)	(30.0, 24.0, 16.0)	29.9	102.6		Ablavar	Chronic portal vein obstruction
6	1.6	F	5.8	(0.9, 1.3, 1.6)	(30.0, 24.0, 12.8)	29.6	102.6		Gadavist	Beta thalassemia with iron overload
7	4.4	F	4.9	(1.1, 1.5, 2.0)	(34.0, 27.2, 16.4)	36.5	97.2		Multihance	Adrenal abnormality
8	1.5	F	2.7	(0.9, 1.3, 2.4)	(30.0, 24.0, 13.9)	22.1	75.1		Gadavist	Sacroccocygeal teratoma, post resection
9	1.2	F	3.7	(0.9, 1.5, 1.8)	(28.0, 19.6, 13.7)	21.1	86.5		Gadavist	Heptablastoma, post resection & chemotherapy
10	4.8	M	4.8	(0.9, 1.2, 1.8)	(28.0, 22.4, 14.4)	29.9	103.5		Gadavist	Clear cell sarcoma, post nephrectomy
11	0.4	F	4.2	(0.7, 1.0, 1.6)	(22.0, 17.6, 12.8)	32.4	111.7		Gadavist	Biliary atresia post Kasai for pre transplant work up
12	3.6	F	2.2	(0.7, 1.0, 1.6)	(32.0, 25.6, 16.0)	29.5	102.2		Gadavist	Wilms' tumor, post resection
13	2.2	M	4.1	(1.0, 1.4, 2.0)	(26.0, 19.5, 13.4)	20.3	70.4		Gadavist	Mature teratoma post resection
14	2.9	F	3.9	(0.8, 1.1, 2.4)	(28.0, 21.0, 19.2)	27.7	97.1		Multihance	CNS tumor with shunt
15	7.7	F	6.1	(1.2, 1.7, 2.4)	(38.0, 30.4, 19.2)	28.8	95.9		Gadavist	Immature teratoma status post resection
16	3.0	M	4.2	(0.9, 1.3, 2.4)	(30.0, 24.0, 16.0)	30.7	102.8		Gadavist	Hepatoblastoma post surgery
17	1.8	F	3.7	(0.8, 1.2, 2.2)	(26.0, 19.5, 13.4)	20.3	70.4		Gadavist	Beta thalassemia with iron overload rule out infection
18	1.1	M	4.5	(1.1, 1.5, 2.4)	(34.0, 27.2, 13.4)	20.7	68.4		Multihance	Diaphragmatic hernia
19	7.1	M	10.2	(1.1, 1.6, 2.4)	(36.0, 28.8, 19.2)	29.0	95.9		Gadavist	Wilms' tumor, post surgery
20	3.7	M	5.0	(0.8, 1.2, 2.0)	(28.0, 22.4, 14.0)	26.2	62.1		Gadavist	Wilms' tumor, right kidney
21	4.6	M	5.6	(0.9, 1.3, 2.4)	(30.0, 24.0, 14.9)	23.3	80.4		Ablavar	Evaluation of vascular malformation
22	0.9	M	7.4	(0.9, 1.3, 2.0)	(30.0, 21.0, 16.0)	27.6	90.0		Gadavist	Left-sided mesoblastic nephroma

Author Manuscript

Author Manuscript

Author Manuscript

Author Manuscript

* FB: free-breathing scan; RT: respiratory triggered/gated scan.

Table 2

Scoring criteria for image assessment.

Score	Overall image quality	Degree of coherent non-cardiac motion ghosts	Hepatic artery	Hepatic vein	Diaphragm	Adrenal gland
1 (Nondiagnostic)	Nondiagnostic assessment of all structures	Coherent ghosts limiting assessment of most structures	Main hepatic artery blurred	Right hepatic vein (RHV) blurred	Diaphragm totally obscured	Adrenal not visualized
2 (Limited)	Limited assessment of several structures	Coherent ghosting limiting assessment of several structures	Right hepatic artery (RHA) blurred	First order branches of RHV blurred	Less than 1/3 of diaphragm seen	One limb of adrenal visualized but blurry
3 (Diagnostic)	All but 1–2 structures can be assessed	Coherent ghosting limiting assessment of 1–2 structures	First order branches of RHA blurred	Sharp first order branches of RHV	1/3–2/3 diaphragm seen	Both limbs visualized but blurry
4 (Good)	All structures can be assessed	Minimally detectable ghosts	Sharp first order branches of RHA	Sharp second order branches of RHV	Larger than 2/3 of diaphragm seen	One limb visualized sharply
5 (Excellent)	Sharp delineation of all structures with high SNR and no non-cardiac motion artifacts	No detectable ghosts	Sharp second order branches of RHA	Branches visualized to within 1 cm of periphery	Entire right hemidiaphragm sharply seen	Both limbs visualized sharply

Table 3

Results of image assessment: mean score and paired Wilcoxon test.

	Mean scores $\pm$ standard deviation				<i>P</i> values of the paired Wilcoxon test (reader 1/reader 2)							
	CS	SG	wAF	RT	SG vs. CS	wAF vs. CS	wAF vs. SG	RT vs. CS	RT vs. SG	RT vs. wAF		
Overall image quality	3.4 $\pm$ 0.8	3.9 $\pm$ 0.7	4.7 $\pm$ 0.5	4.5 $\pm$ 0.7	<0.05/<0.05	<0.05/<0.05	<0.05/<0.05	<0.05/<0.05	<0.05/<0.05	<0.05/<0.05	0.37/0.06	
Motion ghosts	4.1 $\pm$ 0.8	4.2 $\pm$ 0.8	4.6 $\pm$ 0.6	4.6 $\pm$ 0.8	0.16/0.08	<0.05/<0.05	<0.05/<0.05	0.07/<0.05	0.11/<0.05	0.41/0.48		
Hepatic artery	1.7 $\pm$ 0.7	2.1 $\pm$ 0.7	3.2 $\pm$ 0.8	2.3 $\pm$ 1.0	<0.05/<0.05	<0.05/<0.05	<0.05/<0.05	<0.05/<0.05	0.72/0.09	<0.05/<0.05		
Hepatic vein	2.3 $\pm$ 1.4	3.1 $\pm$ 1.4	4.5 $\pm$ 1.0	4.3 $\pm$ 1.1	<0.05/<0.05	<0.05/<0.05	<0.05/<0.05	<0.05/<0.05	<0.05/<0.05	0.89/0.14		
Diaphragm	1.8 $\pm$ 0.8	2.1 $\pm$ 0.9	2.9 $\pm$ 1.2	3.0 $\pm$ 1.3	<0.05/0.21	<0.05/<0.05	<0.05/<0.05	<0.05/<0.05	<0.05/<0.05	0.22/0.76		
Adrenal gland	3.3 $\pm$ 1.0	3.6 $\pm$ 1.0	4.2 $\pm$ 0.8	4.2 $\pm$ 1.0	<0.05/0.10	<0.05/<0.05	<0.05/<0.05	<0.05/<0.05	<0.05/<0.05	0.76/0.41		

* CS: conventional parallel imaging & compressed sensing; SG: soft-gated accelerated imaging; wAF: soft-gated autofocusing; RT: respiratory triggered/gated.

Table 4

Inter-observer agreement results using weighted kappa coefficient between reader 1 and reader 2.

	CS	SG	wAF	RT
Overall image quality	moderate (0.56)	moderate (0.55)	fair (0.38)	substantial (0.70)
Motion ghosts	fair (0.33)	fair (0.35)	moderate (0.6)	moderate (0.58)
Hepatic artery	moderate (0.49)	moderate (0.56)	moderate (0.5)	substantial (0.63)
Hepatic vein	substantial (0.76)	substantial (0.73)	substantial (0.78)	almost perfect (1.00)
Diaphragm	slight (0.2)	moderate (0.57)	moderate (0.54)	substantial (0.70)
Adrenal gland	moderate (0.52)	moderate (0.46)	moderate (0.57)	substantial (0.67)

* CS: conventional parallel imaging & compressed sensing; SG: soft-gated accelerated imaging; wAF: soft-gated autofocusing; RT: respiratory triggered/gated.