Highly Accelerated MRI by Sensitivity Encoding with Skipped Phase Encoding and Edge Deghosting (SEN-SPEED)

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Introduction

MRI scan time can be reduced by many fast imaging methods such as SENSE [1], and Skipped Phase Encoding and Edge Deghosting (SPEED) [2]. SENSE uses multiple receiver coils in parallel to achieve sensitivity encoding. However, because of noise amplification at a high acceleration factor [3], SENSE is often used with an acceleration factor of 2 although larger values are possible. Unlike SENSE, SPEED is a single-coil fast imaging method based on a different principle. It is efficient but does not take advantage of multiple coils to accelerate MRI further. To overcome the limits of SENSE and SPEED, this paper presents a new fast imaging method combining SENSE with SPEED and thus is named SEN-SPEED.

Methods

If k-space is sampled at every Nth phase encoding (PE) step into a sparse data set, it can be Fourier transformed into a ghosted image, which is associated with N aliasing ghosts and as such has ghost overlapping up to N layers. Each pixel in the ghosted image is a superposition of N pixels of a desired image reconstructed from full k-space data. In SENSE, by making use of the fact that signal in each ghosted image is likely weighted by different coil sensitivity, the signal superposition can be unfolded with at least N ghosted images [1]. However, frequently used acceleration factor of SENSE is currently only 2 to ensure image quality in clinical practice because noise is amplified as scan time significantly reduces [3].

On the other hand, SPEED uses Skipped Phase Encoding and Edge Deghosting to reduce scan time [2]. For example, 3 interleaved data sets are obtained by sampling k-space at every 5th PE step with 3 different relative shift sizes chosen from 0,1,2,3, and 4. The 3 data sets are Fourier transformed and high-pass filtered into 3 ghosted edge maps. By modeling them with a bilayer structure, a deghosted edge map can be solved with a deghosting algorithm based on a least-square-error (LSE) solution. The deghosted edge map is inverse-filtered into a final deghosted image. In this case, SPEED obtains 3 equations through 3 interleaved samplings and reduces scan time by a factor of 3/5. SPEED is used so far with single coil and as such does not take advantage of multiple coils as SENSE does. This is a relative disadvantage.

$$E_{1,d} = S_1^{n1} P_d^{n1} G_{n1} + S_1^{n2} P_d^{n2} G_{n2} \quad (1)$$

$$E_{2,d} = S_2^{n1} P_d^{n1} G_{n1} + S_2^{n2} P_d^{n2} G_{n2} \quad (2)$$

$$E_{3,d} = S_3^{n1} P_d^{n1} G_{n1} + S_3^{n2} P_d^{n2} G_{n2} \quad (3)$$

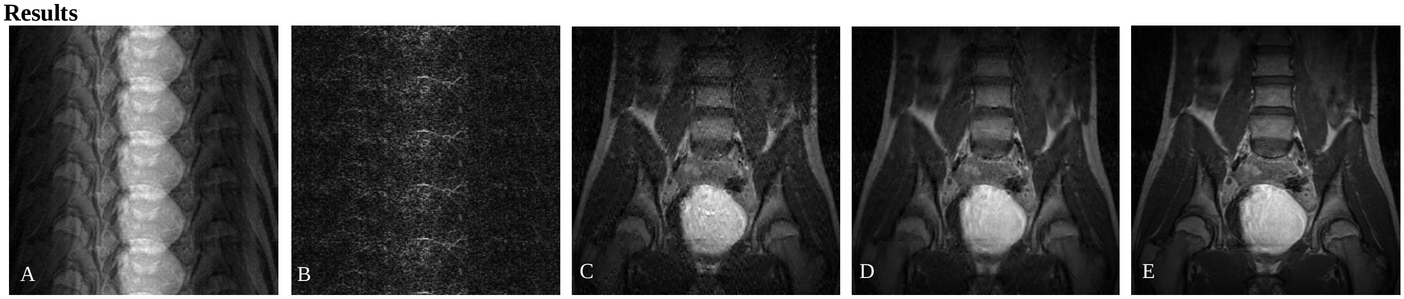
$$E_{4,d} = S_4^{n1} P_d^{n1} G_{n1} + S_4^{n2} P_d^{n2} G_{n2} \quad (4)$$

To overcome the limits of SENSE and SPEED, we combined them into a new method named SEN-SPEED. Unlike SPEED, SEN-SPEED obtains multiple equations through one sparse sampling by using multiple coils in parallel. SEN-SPEED samples data as SENSE does but processes the data as SPEED does. For example, with a 4-receiver-coil array, sampling k-space at every Nth PE step with a relative shift size of d achieves an acceleration factor of N and yields 4 ghosted images with N aliasing ghosts. If N = 5, the application of a differential filter to the ghosted images would reduce ghost overlapping layers from N=5 to 2. Since coil sensitivity is usually varying slowly, its spatial differential is always negligible. Therefore, the filtered ghosted edge maps can be described by equations (1-4), where G_{n1} and G_{n2} are the 2 dominating edge ghosts; P_d^n a ghost phasor known to have a form of $[\exp(i2\pi k/N)]^n$, where n = 0,1…N-1 is the order of ghost depending on its relative location; and S_d^n denotes coil sensitivity factor for the edge ghost of nth order. Note that P_d^n is a SPEED factor and S_d^n is a SENSE factor.

Since n1 ≠ n2, the total number of possible pairs of (n1, n2) is $N(N-1)/2 = 10$. By trying all of the pairs, the correct solutions of (G_{n1}, G_{n2}) and (n1, n2) can be found by minimizing LSE at each pixel. The resolved edge ghosts (G_{n1}, G_{n2}) can be sorted out according to associated (n1, n2) and as such can yield 5 edge ghosts. Finally, they are registered spatially and inverse-filtered to yield a deghosted image. The central k-space data (*e.g.* 32 out of 256) sampled to measure coil sensitivity profiles are also used in the inverse filtering to avoid artifacts caused by dividing numbers close to zero.

Although the 2-layer model is usually applicable in SEN-SPEED, more layers in the model can be used to yield improved result. To do so, a series of deghosted edge maps are obtained with different overlapping models. In the example given previously, 4 ghosted images can be used to yield 4 deghosted edge maps based on 4 different models from a 0-layer model to a 3-layer model. The 4 edge maps can be optimally averaged and inverse-filtered into a final image with improved quality. A standard spin-echo coronal spine scan was performed on a clinical 1.5 T scanner with 4 coils, and full k-space data were saved. The data were sparsely sampled and processed by SEN-SPEED to demonstrate its feasibility as shown below.

Results



A is one of the 4 ghosted images from the 4 coils with a PE skip size N=5. B is the edge map of A. C is the deghosted image based on a 2-layer-model. D is the optimally averaged deghosted image based on 4 different overlapping models. With an acceleration factor of 5, D shows comparable result to the gold standard E reconstructed from full k-space data. A-E are actually complex but shown here in magnitude for easy visualization.

Conclusion

In this work, we presented a fast imaging strategy named SEN-SPEED. By combining SENSE and SPEED, SEN-SPEED can reduce MRI scan time by a high acceleration factor (typically 5) and can yield results comparable to the “gold standard” reconstructed from full k-space data.

References

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