Improved MR Image Magnification by Generalized Interpolation of Complex Data

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Introduction

Image viewing and manipulation is common on MR scanners and workstations as a convenient means of magnifying, rotating, and shifting of the data for closer inspection. When an image is pulled out of a database and interaction with this data requires information to be made available off of the Cartesian grid, interpolation is used to determine the missing information. A cubic interpolation kernel is often used because it does not suffer from the same artifacts that can be caused by nearest neighbor or linear interpolation, while still being small enough in size to be computationally reasonable. This limited kernel support can still have a low-pass effect on the image however. Because of this, image reconstructions often zero-pad acquired k-space data and insert what is equivalent to a sinc-interpolated image into the database. Evaluated here, is an alternative where an acquired-size, complex image is made available to the display and generalized interpolation is used on this data for improved spatial resolution.

Methods

To quantify the overall impact of the interpolation procedures described below, each image is magnified by a factor ranging from 1.1 to 4.0 times the original x and y dimensions in increments of 0.1. For example, a 256x256 image magnified by 1.5 in this experiment will yield a 384x384 image. As MR reconstruction often provides zero-padded DFT-based interpolated images today, this will be used as a standard of reference to compare against.

The first interpolation kernel considered is the four-point cubic spline (1) which, implemented separably, requires eight multiply-adds per pixel of the output image. The second is a generalized interpolation method that involves pre-filtering of the image data, followed by interpolation of the filtered image. From a category of functions that give maximal order interpolation for a minimal amount of support (MOMS) [1], the four-point cubic o-MOMS (2) function is used as the interpolant. The pre-filter applied is specifically designed for use with this interpolant and is well described in [2]. Due to the equivalent support, the compute time for both methods will be the same with exception of the additional pre-filtering step in the o-MOMS processing, which becomes negligible as the size of the magnified image increases.

$$cubic(x)=\begin{cases}|x|^3-2|x|^2+1 & 0\le|x|<1\\ -|x|^3+5|x|^2-8|x|+4 & 1\le|x|<2\end{cases} \quad (1)$$

$$oMOMS^3(x)=\begin{cases}\frac{1}{2}|x|^3-|x|^2+\frac{1}{14}|x|+\frac{13}{21} & 0\le|x|<1\\ \frac{-1}{6}|x|^3+|x|^2-\frac{85}{42}|x|+\frac{29}{21} & 1\le|x|<2\end{cases} \quad (2)$$

In addition to the interpolation functions considered above, the impact of performing magnification on the magnitude image versus the magnification of real and imaginary components separately is compared. The interpolation time will take twice as long for this complex case.

Raw data sets were acquired for retrospective reconstruction from a phantom with a radial structure, the ACR phantom (Fig 1a), and a T1-weighted brain. All three data sets have a 256x256 acquisition size, and were collected from a GE Signa HDx 1.5 T scanner with EchoSpeed gradients (GE Healthcare, Waukesha, WI, United States) using a single channel head coil.

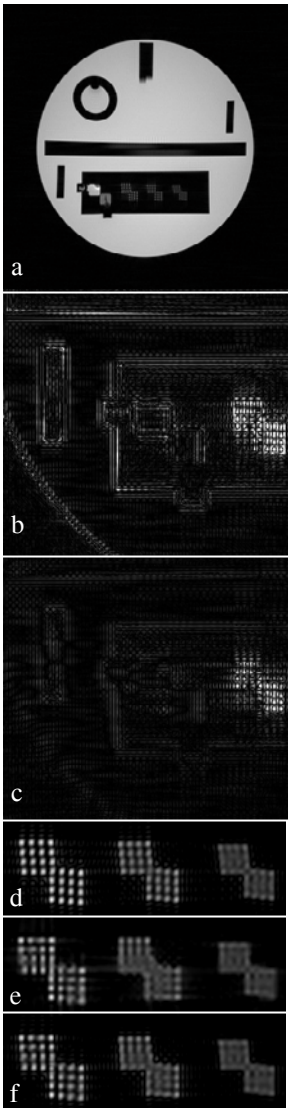

Fig 1: (a)ACR phantom image. Difference of complex sinc 3.0x magnification compared to (b) magnitude cubic, (c) complex oMOMS. ACR Resolution holes after 3.0x zoom of (d) sinc, (e) magnitude cubic, (f) complex oMOMS.

Results

For each magnification performed, a measurement was made (3) to evaluate how well the result of an interpolation experiment (g) corresponds to the expected result [2], which in this case is the image from zero-padded interpolation (f). Table 1 contains the mean and standard deviation of this measurement across the range of magnifications (1.1 to 4.0x) for each interpolation type. As shown for the ACR case in Fig 1b and 1c, and consistent across all three images (radial, ACR & brain), using complex data along with generalized interpolation improved the likeness to results from a complex, sinc interpolation. For visual comparison, the ACR phantom resolution holes from a 3.0x magnification are displayed for the complex sinc (Fig 1d), cubic interpolation of magnitude data (Fig 1e), and o-MOMS interpolation of complex data (Fig 1f).

Table 1: 1.1-4.0x magnification results from Eq. 3, in mean (std. dev.)

Interpolation	Radial	ACR	Brain
Cubic (magnitude)	54.6 (0.127)	69.1 (0.256)	61.4 (0.205)
o-MOMS^3 (magnitude)	61.0 (0.034)	71.9 (0.144)	64.7 (0.104)
Cubic (complex)	55.5 (0.139)	75.1 (0.413)	65.7 (0.288)
o-MOMS^3 (complex)	62.9 (0.026)	82.7 (0.137)	72.9 (0.102)

$$10\log\left(\sum_{x,y=1}^{len_{x,y}} f_{x,y}^2 \Big/ \sum_{x,y=1}^{len_{x,y}} \left(f_{x,y}-g_{x,y}\right)^2\right) \quad (3)$$

Discussion

Improved magnification of MR images has been demonstrated through higher order interpolation of complex data. While applied in two dimensions for this analysis, the separable interpolation can be used for any number of dimensions of data being magnified.

References

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[2] Thevenaz, et. al. *Interpolation Revisited.* IEEE Transactions on Medical Imaging; 2000; 19:739-758.