JULY 12–16 2020 VIRTUAL
JOINT AAPM | COMP MEETING
EASTERN TIME [GMT-4]

Fast DTI using Deep Learning based on Cartesian and non-Cartesian Undersampling Schemes

Z. Gao[1], T. Arsenault[2], Z. Chang[2]
1Duke Kunshan University, Jiangsu, China
2Duke University, Durham, United States

DukeHealth – 昆山杜克大学 DUKE KUNSHAN UNIVERSITY

INTRODUCTION

Diffusion Tensor Imaging (DTI) is a specific MRI sequence to make use of the diffusion of water molecules to generate contrast for tissues; however, the DTI requires long acquisition time, which shadows its clinical applications. To accelerate DTI acquisition, deep learning (DL) has been proposed to undersample k-space and then reconstruct a complete MR image.

Currently, few data are available about the undersampling schemes of fast DTI using DL. In this study, the undersampling schemes are investigated in DL to keep sufficient data for later reconstruction on the basis of ensuring the optimal image quality.

AIM

We study the feasibility of the fast DTI techniques. Also, we aimed to compare the acquisition speed of Cartesian undersampling scheme against that of non-Cartesian undersampling scheme on DC-CNN network on the basis of preserving the image quality and biological information for diffusion tensor imaging (DTI).

METHOD

- Seventeen DTI brain scans from the TCIA [1,2] were used, each with twelve diffusion-weighted data sets with b = 1,000 s/mm^2 and one with b = 0 s/mm^2.
- For each DTI data set, three slices were randomly selected for evaluation, and the remaining data were used for the training reconstruction models using the DC-CNN [3] network.
- The training data were sampled using quarter and one-sixth sampled Cartesian undersampling schemes, and one-sixth and one-eighth sampled non-Cartesian undersampling schemes first, as illustrated in Figure 1. Then the data will go through the DC-CNN network for training purpose.
- The reconstructed images by neural network were compared against the reference images using total relative error (TRE) and mean structure similarity (MSSIM) for reconstruction accuracy, as well as Fractional Anisotropy (FA), scaled Relative Anisotropy (sRA) maps and principle direction maps for biological information.

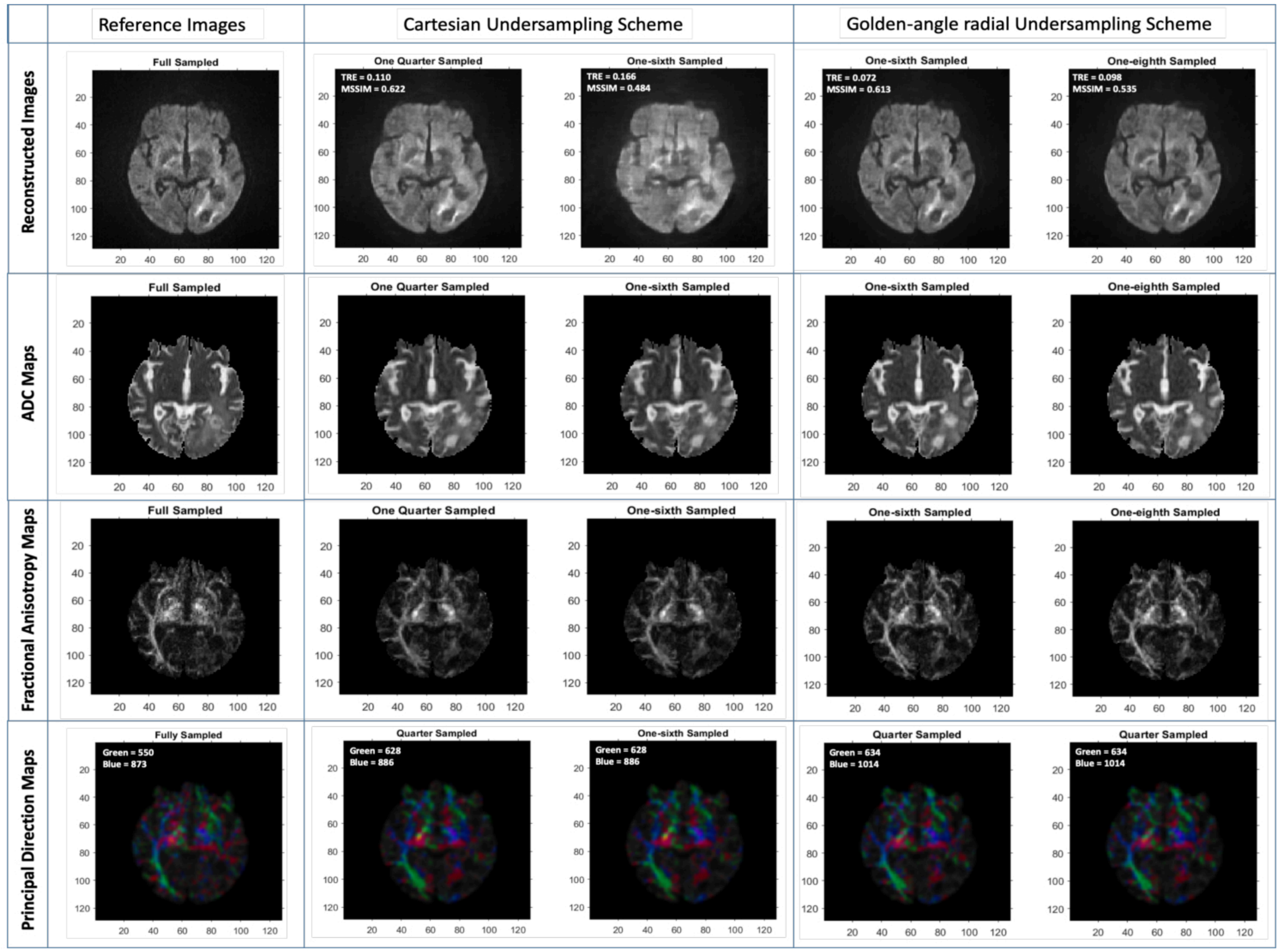
RESULTS

Figure 1 demonstrated the reconstructed DTI by neural networks using 1/4 and 1/6 sampled Cartesian schemes, and 1/6 and 1/8 sampled non-Cartesian golden-angle radial schemes, and their ADC Maps, Fractional Anisotropy, and principle directions maps compared against the fully sampled k-space images.

For image quality, the reconstructed images by the DC-CNN network using the 16.7% and 12.5% non-Cartesian radial undersampling scheme are measured to have TRE values of 0.068 and 0.088, MSSIM values of 0.60 and 0.51; in contrast, the 25% and 16.7% Cartesian undersampling yielded TRE values of 0.097 and 0.042, MSSIM values of 0.60 and 0.47.

For biological information, ADC and FA maps derived by non-Cartesian radial undersampling and Cartesian undersampling all show comparable to the reference ADC and FA maps that was derived from the fully-sampled k-space data. In principal direction maps, the red, green, and blue colors represent the direction of diffusion in the left-right, anterior-posterior, and superior-inferior directions.

Figure 1. Comparison of the **reconstructed images, Fractional Anisotropy,** and **principle directions maps**



CONCLUSIONS

The reconstructed diffusion-weighted MR images by DC-CNN network demonstrated the feasibility of the fast DTI techniques. Also, the results presented in this work suggest that non-Cartesian radial undersampling outperformed the Cartesian undersampling on accelerating the DTI acquisition by DC-CNN network on the basis of ensuring the image quality and biological information.

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ACKNOWLEDGEMENTS

Thanks to The Cancer Imaging Archive (TCIA) for generous contribution to opening the data source for relevant researches.

CONTACT INFORMATION

E-mail: zhengxin.gao@dukekunshan.edu.cn