Multichannel input pixelwise regression 3D U-Nets for medical image estimation with 3 applications in brain MRI

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Summary

- We propose the use of the multichannel input pixelwise regression 3D U-Net (rUNet) for estimation of medical images.
- Our findings demonstrate that this approach is robust and versatile and can be applied on 3 applications:
  1. predicting a pending MRI examination of patients with Alzheimer's disease based on previous rounds of imaging
  2. performing medical image reconstruction (parametric mapping) in diffusion MRI
  3. estimation of one type of MRI examination from a collection of other types.
- Results demonstrate that the rUNet represents a single deep learning architecture capable of solving a variety of image estimation problems.

Introduction

- The U-Net[1] is a robust deep learning architecture designed for semantic segmentation in medical imaging.
- In this paper, we apply the pixel-wise regression U-Net to medical image estimation, which has been previously applied to satellite images[2].
- We propose the use of multichannel input 3D U-Nets (rUNet) that utilize multiple input volumes for prediction in three tasks.
- We also compare multichannel to single channel input.

Methods

- **The U-Net model.** We use a 5-level 3D U-Net architecture, with Leaky ReLU activation ($\alpha = 0.2$), learning rate ($\alpha = 10{-}5$), Adam optimizer, mean absolute average error (MAE) loss function, z-score intensity normalization, early stopping, and co-registered volumes resized to 128×128×128. Applications 1 and 3 included skull stripping. Batch size was 3 in applications 1 and 3, and 1 in application 2.
- **Measurements.** We compare all approaches with mean squared error (MSE), MAE, structural similarity index measure (SSIM), and peak signal to noise ratio (PSNR).
- **Longitudinal image estimation.** Data was used from the Alzheimer's Disease (AD) Neuroimaging Initiative database. 88 AD subjects with 4 longitudinal MRI scans at screening (SC), month 6 (M06), month 12 (M12) and month 24 (M24) were used, with 70 subjects included for training and 18 for testing. We evaluated using (SC, M06, M12), (M06, M12), and (M12) to predict the M24 volume.
- **Diffusion image reconstruction.** Data was obtained from The Human Connectome project, where we used 19 MR diffusion tensor exams: 16 training, 3 testing.
  - The Diffusion toolkit was used to process the 4D diffusion exam into fractional anisotropy (FA) and apparent diffusion coefficient (ADC) volumes for the target images.
  - Data augmentation including rotation with random angle $[-12^\circ, 12^\circ]$ and a random spatial scaling factor [0.9, 1.1].

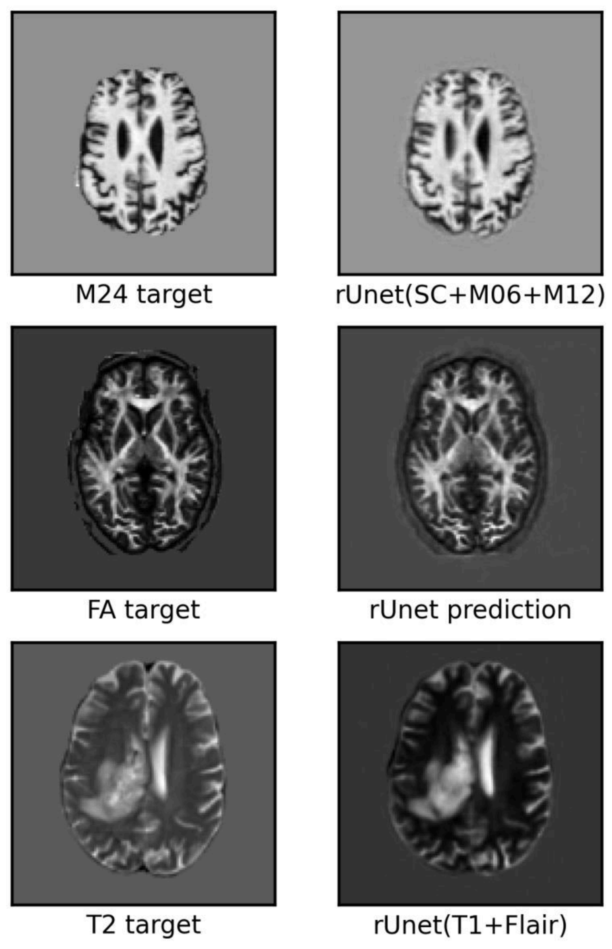

Figure 1: Qualitative Results.

- **T1/T2 estimation.** Data was obtained from BraTS'18-'20, containing T1, T2 and T2-FLAIR volumes from 1044 training and 261 testing subjects.
  - We have tested estimating T2 from T1 and from T1 & T2-FLAIR, and estimating T1 from T2 and from T2 & T2-FLAIR.

Table 1: Quantitative Results.

Task	MSE ↓	MAE ↓	SSIM ↑	PSNR ↑
SC+M06+M12→M24	0.0058	1.952	0.967	**35.056**
M06+M12→M24	**0.0056**	**1.269**	**0.968**	34.937
M12→M24	0.0065	1.756	0.961	34.292
Diffusion→ADC	0.0253	1.239	0.919	35.423
Diffusion→FA	0.0136	1.258	0.945	35.980
T1+T2-Flair→T2	**0.0043**	2.211	0.985	**42.530**
T1→T2	0.0049	**2.040**	**0.986**	41.780
T2+T2-Flair→T1	**0.0030**	**0.900**	**0.989**	**42.604**
T2→T1	0.0041	1.137	0.986	40.872

Results and Discussion

- Table 1 and Figure 1 demonstrate improvements from the use of multichannel input relative to single channel input in applications 1 & 3.
- Diffusion parametric mapping demonstrated that, we get robust results with very small datasets employing data augmentation.
- Results indicate that the 3D multichannel rUNet is a robust and flexible architecture capable of handling a diverse array of image estimation problems
- The AD application predicts future rounds of imaging, potentially providing useful information for clinicians in charge of managing a patient's care.
- The diffusion application demonstrates potential for the rUNet in image reconstruction applications, supporting the creation of learned parametric maps that can target any given spatially distributed anatomical or physiological measurement of interest.
- The diffusion and T1/T2 applications demonstrate the potential for performing image estimation nearly instantly, thus having potential in emergency and critical care circumstances where near instant reconstruction/estimation for clinicians is valuable.

References

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Acknowledgments

This work was supported through a Canada Research Chair grant (231266), a CFI and NSRIT grant, and an NSERC Discovery Grant to JL. Data collection and sharing was funded by the Alzheimer's Disease Neuroimaging Initiative (ADNI) (NIH Grant U01 AG024904) and DOD ADNI (W81XWH-12-2-0012).

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MIDL Lübeck 2021