Automated Estimation of CBF and ATT from Multi-PLD ASL Using a Three-Dimensional Convolutional Neural Network

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Introduction & Purpose

Arterial Spin Labeling

- Arterial spin labeling (ASL) is one of the magnetic resonance (MR) perfusion imaging methods. Cerebral blood flow (CBF) can be directly quantified using ASL by accounting for signal decay, timing parameters, and equilibrium magnetization. Arterial transit time (ATT) is the time required for the bolus of blood to travel from the labeled location to its final location such as a brain tissue. ATT can be quantified using a post-labeling delay (PLD) between the label and the acquisition of the image.

Multi-PLD PCASL

- Multiple post labeling delay (PLD) ASL has been used to estimate CBF and ATT more accurately with multiple PLDs (Figure 1).
  - ✓ Longer scan time

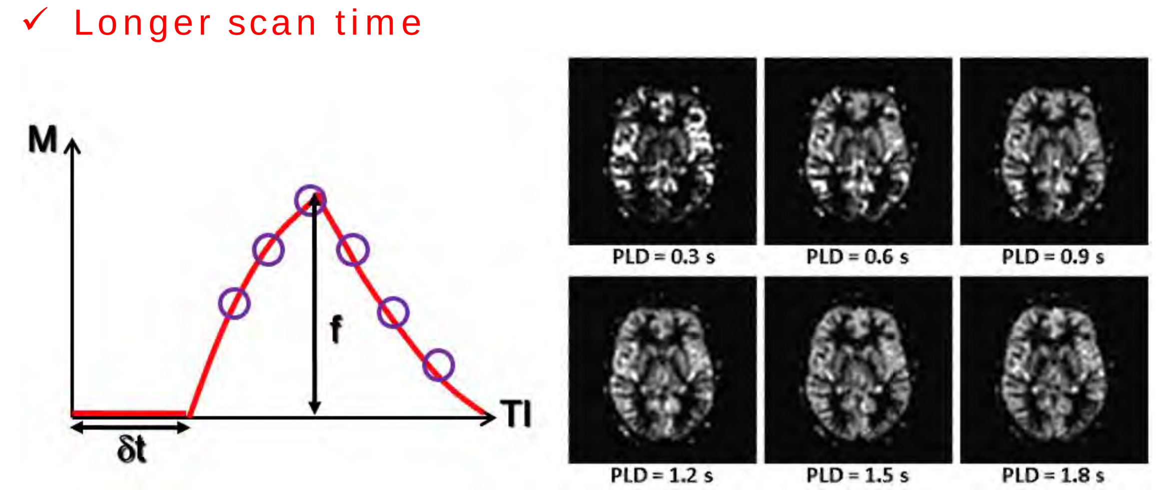

Figure 1. ASL standard curve (left)[1] and PCASL images by different PLDs. Each PCASL image shows different magnetization between the label and control images.

Purpose

- A hierarchically structured CNN was developed to estimate both CBF and ATT maps with the reduced numbers of PLDs or averages in multi-PLD PCASL, which may allow total scan time reduction of multi-PLD PCASL.

Acquisitions & Reference Model

Forty-eight subjects (age: 67.31±6.80 years, M/F: 10/38) from the Wake Forest Alzheimer's Disease Research Center had MRI including a multi-PLD PCASL sequence on a 3T Siemens Skyra MRI with a 32-channel head coil (Siemens, Erlangen, Germany). The subjects included 38 mild cognitive impairment (MCI), 25 hypertension, and 7 type 2 diabetic subjects.

- Total 6 TIs were collected from 1800ms, with increments of 600ms and 6 averages per TI. The duration of PCASL labeling was 1800ms except the shortest TI that had 1700ms. Corresponding PLDs were [100ms, 600ms, 1200ms, 1800ms, 2400ms, and 3000ms].
- Each TI had minimum TR: [2900ms, 3500ms, 4100ms, 4700ms, 5300ms, and 5900ms][2]. The scan time for all six TIs were 5 minutes 21 seconds.
- A single-shot 2D EPI acquisition was used to cover the whole brain (56x70x36 matrix size, 3x3x4mm resolution, and 27.5ms delay between slices). To create the ground truth reference images for CBF and ATT, a voxel-wise non-linear model fitting was applied using the ASL kinetic model[1].

Non-Linear Model Fitting

- A conventional method to estimate CBF and ATT.
- The acquired data is nonlinearly fitted to the ASL standard model using the prefusion weighted images form multiple PLDs.
- The calculated CBF and ATT maps from the non-linear fitting method with a full dataset which contains 6 PLDs and 6 averages were used for the reference standard for each subject.

Methods

We hypothesized that there still be room for improvement regarding acquisition time because multiple PLDs may include redundant perfusion information. There has been emerging development in using a deep learning-based approach in the medical field including recovering estimation from under-sample dataset. In this respect, the implementation of CNN can potentially recover the under-sampled multi-PLD PCASL perfusion maps.

Hierarchically Structured Convolutional Neural Network

- Based on the ASL standard model, CBF depends on ATT, but ATT is not directly related to CBF[1-2].
- We implemented a 3D hierarchically structured CNN (H-CNN) model to estimate CBF and ATT maps in respect to their physiological relationship (Figures 2 and 3).

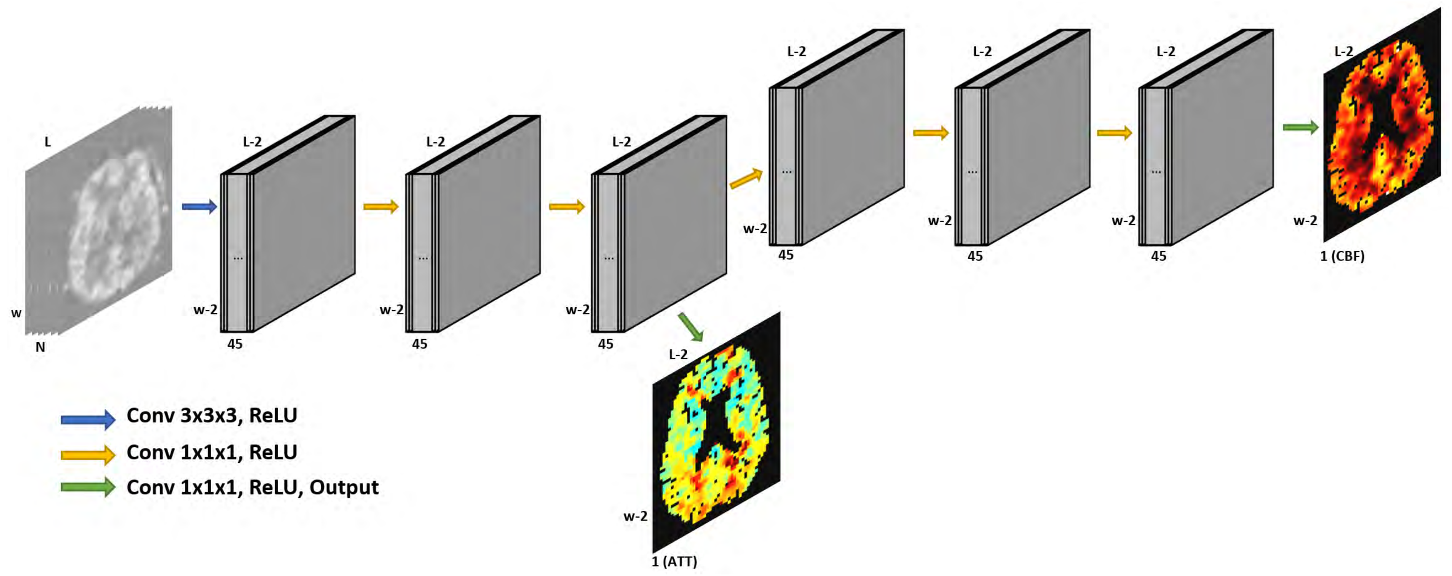

Figure 2. The structure of hierarchical CNN (H-CNN). *L* x *W* x *H* is the size of the PWI (the *H* dimension is not shown), and *N* denotes the number of PLDs.

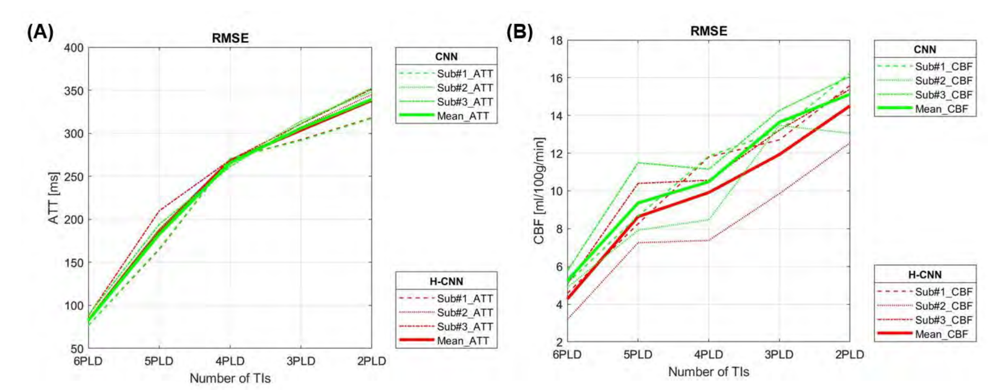

Figure 3. The overall RMSEs of standard CNN (green) and H-CNN (red) with the reduced numbers of PLDs: (A) ATT estimation and (B) CBF estimation.

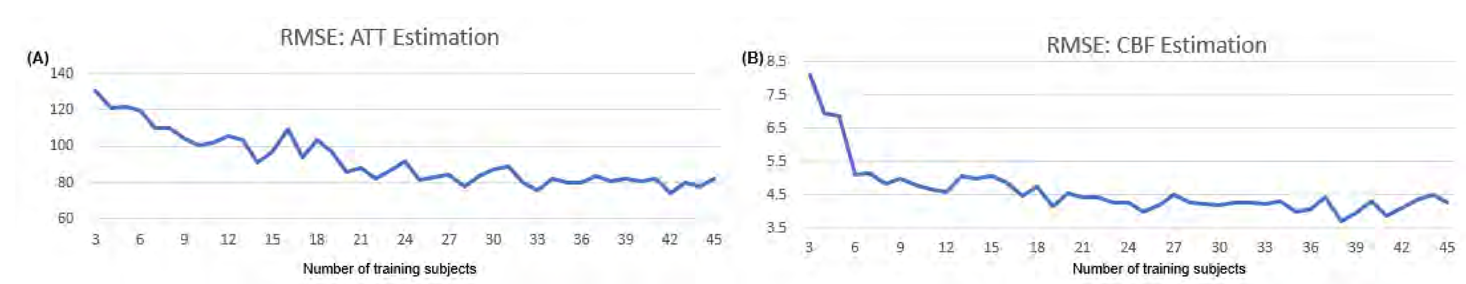

Figure 4. The overall RMSEs of H-CNN by the number of training subjects: (A) ATT estimation and (B) CBF estimation.

Selected PLDs	Time Saving (Total Scan Time)
6 PLDs (all)	0 % (5m 21s)
5 PLDs (1, 2, 3, 4, 6th)	20.08 % (4m 17s)
4 PLDs (1, 3, 4, 5th)	35.60 % (3m 27s)
3 PLDs (1, 3, 4th)	53.41 % (2m 30s)
2 PLDs (1, 4th)	71.21% (1m 32s)
Number of Averages	**Time Saving (Total Scan Time)**
6	0 % (5m 21s)
5	16.67 % (4m 28s)
4	33.33 % (3m 24s)
3	50.00 % (2m 41s)
2	66.67 % (1m 47s)
1	83.33 % (53s)

Table 1. Time saving by selected PLDs or Averages for H-CNN

Experiments

- 45 randomly chosen training subjects (Figure 4)
- 3 test subjects

To test if the reduced number of PLDs or averages can be recovered in the H-CNN, the PWIs with the reduced number of PLDs or averages were used for the training.

Data Reduction Scheme

- PLDs: Every single combination of PLDs to avoid any bias for choosing PLDs.
- Averages: First *N* averages were sequentially selected from the dataset.

Results

Based on the overall MAE, the H-CNN outperforms the model fitting method when the number of PLDs or averages was reduced (Figures 5, 6, and 7).

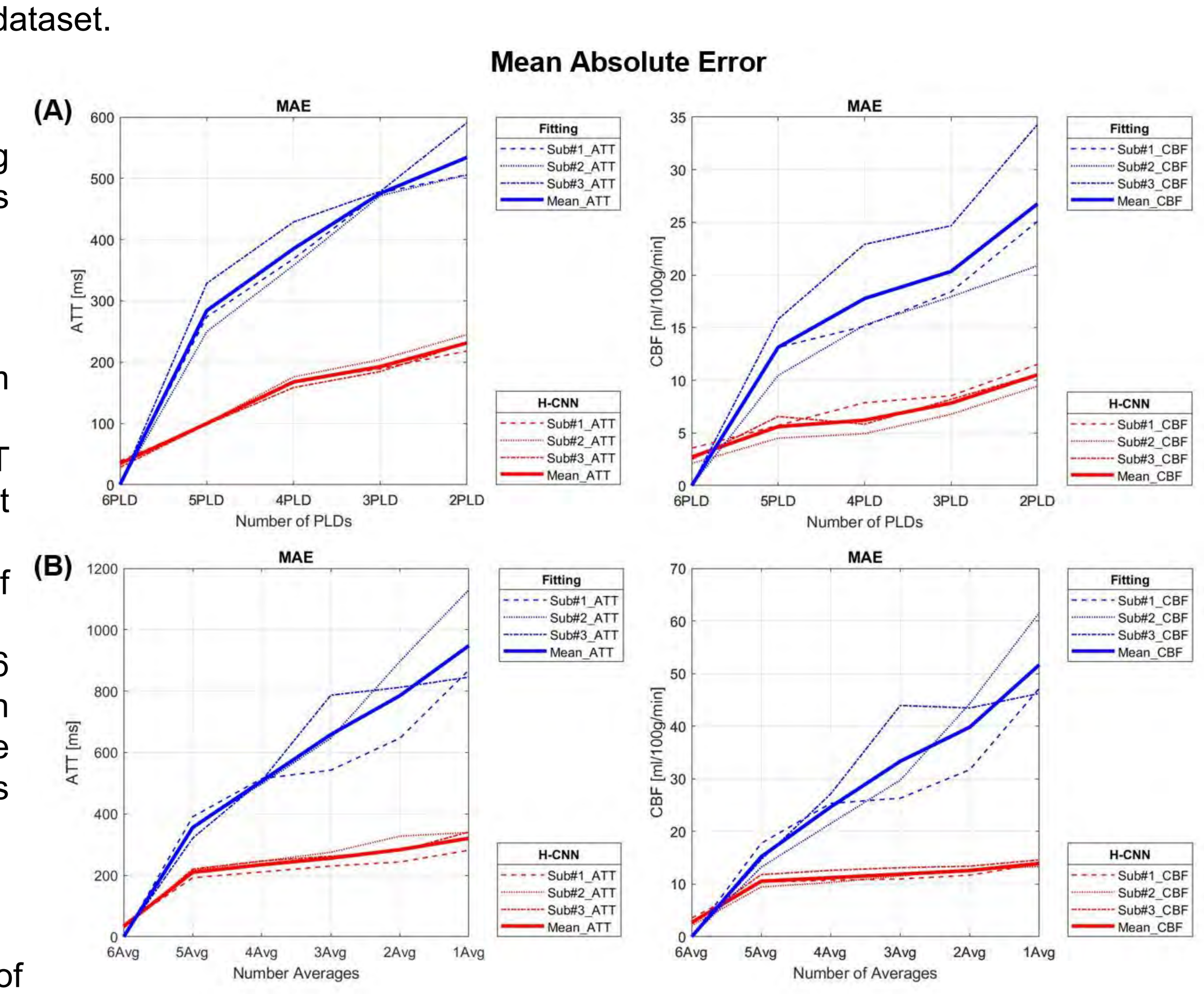

Figure 5. The overall MAEs of the estimated CBF and ATT maps from the non-linear fitting (blue) and H-CNN (red) using (A) the reduced number of PLDs and (B) the reduced number of averages.

Discussion

- A H-CNN model was developed to estimate CBF and ATT from multi-PLD PCASL with the reduced number of PLDs or averages.
- The developed H-CNN successfully estimated both CBF and ATT maps using the reduced number of PLDs without significant discrepancy.
- This study may have a potential that provides the ideal choices of PLDs.
- Based on the estimation errors from the reduced averages, 6 averages may be optimum average required in this acquisition scheme, but this work showed that less averages can be used in the processing to improve image quality when a part of acquisition is motion corrupted.

Conclusion

In conclusion, the reported results showed that a smaller number of PLDs or averages can be used in the processing without significant discrepancy from the reference, which may allow a total scan time reduction of multi-PLD PCASL scheme (Table 1 and Figure 6).

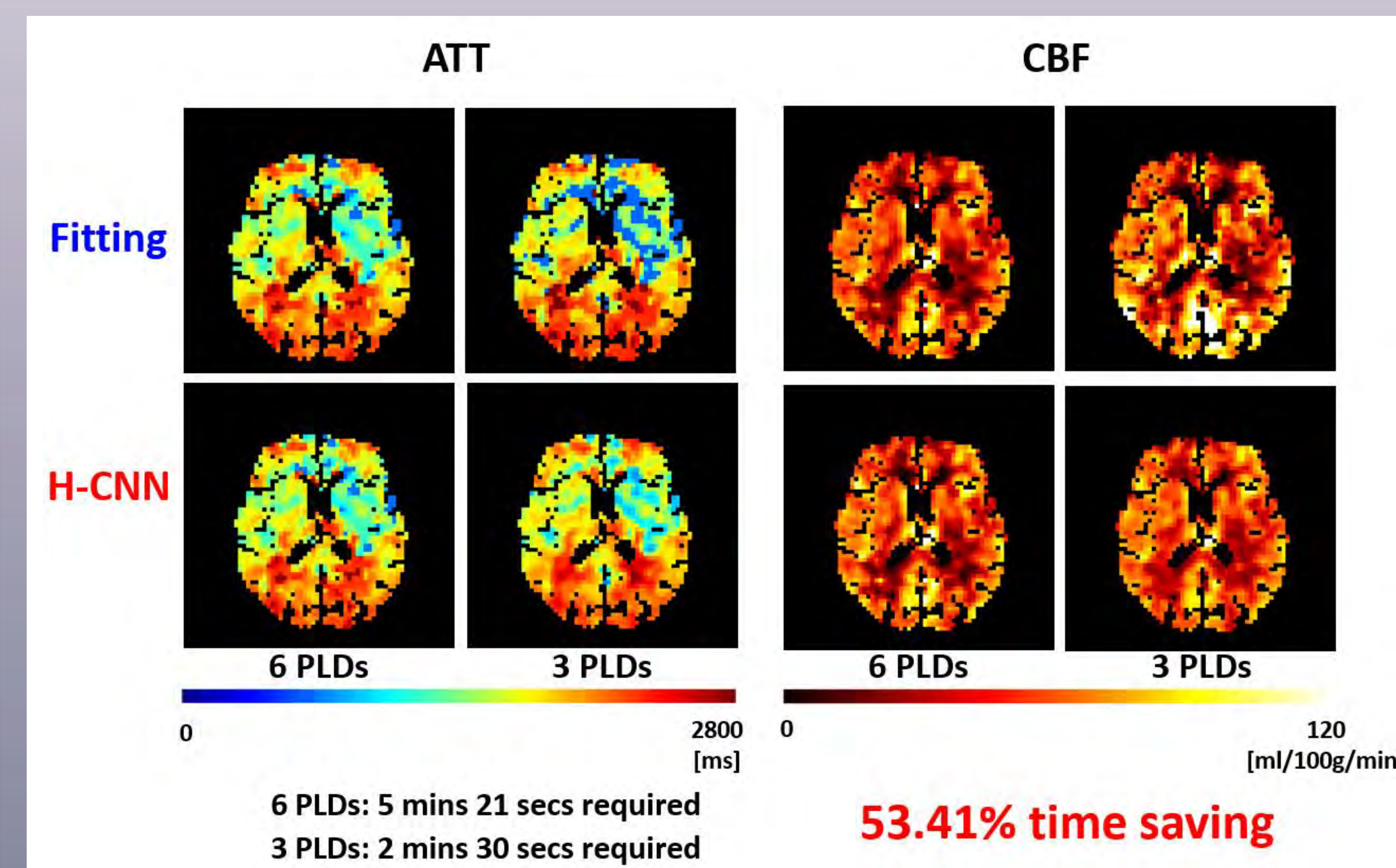

Figure 6. Highlighted results showing the estimated CBF and ATT maps from the nonlinear model fitting and H-CNN. Both CBF and ATT maps can be estimated using the reduced number of PLDs without significant discrepancy.

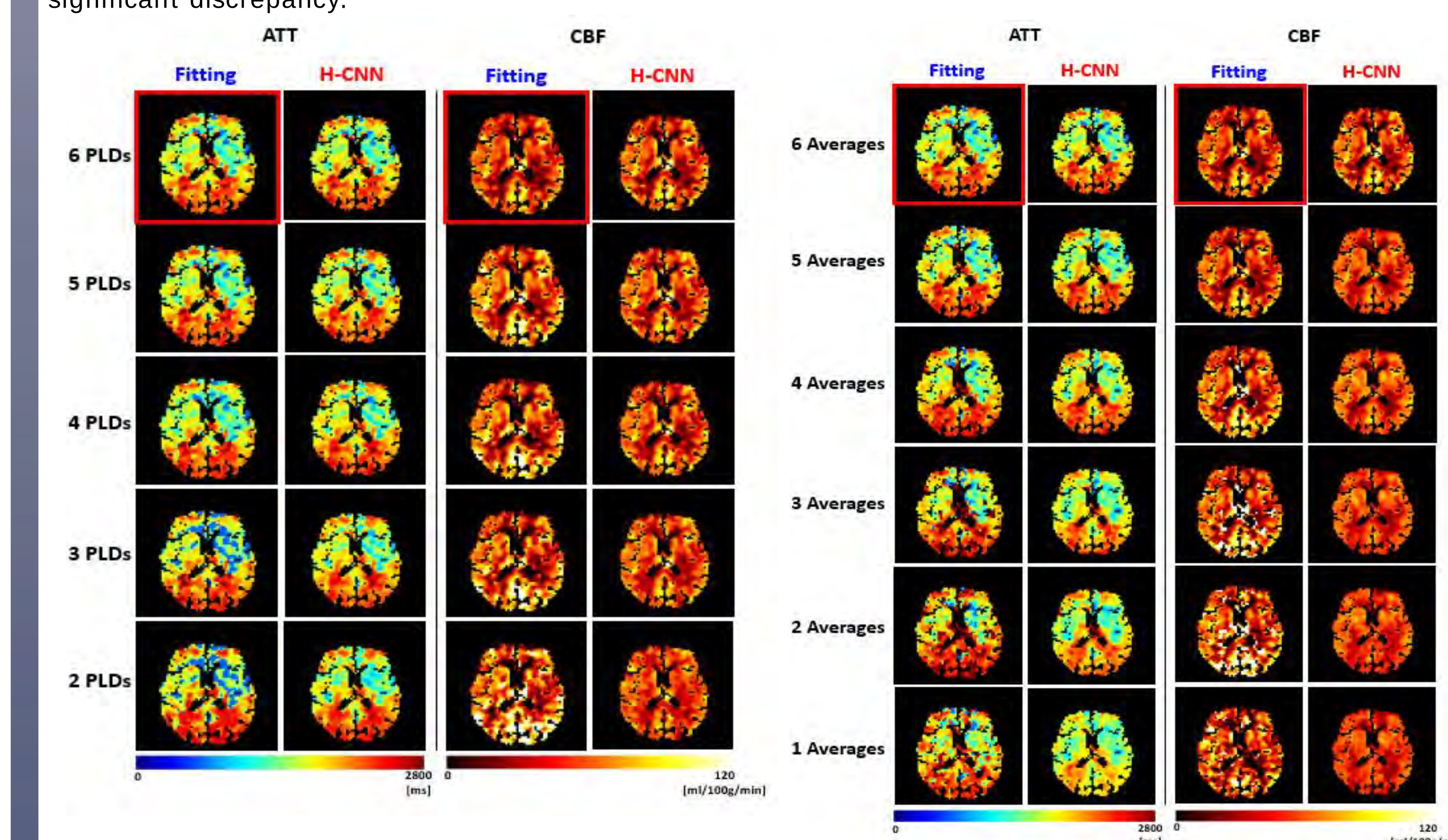

Figure 7. Estimated CBF and ATT maps from the nonlinear model fitting and H-CNN using (A) the reduced number of PLDs and (B) the reduced number of averages. CBF and ATT maps (red boxes) from the nonlinear model fitting with 6 PLDs and 6 averages are the ground truth references of the subject who showed the longest mean ATT among 3 test subjects.

Clinical Applications

- Scan time saving (Table1 and Figure 6)
- Increase SNR
- Recover corrupted scan (Figure 8)

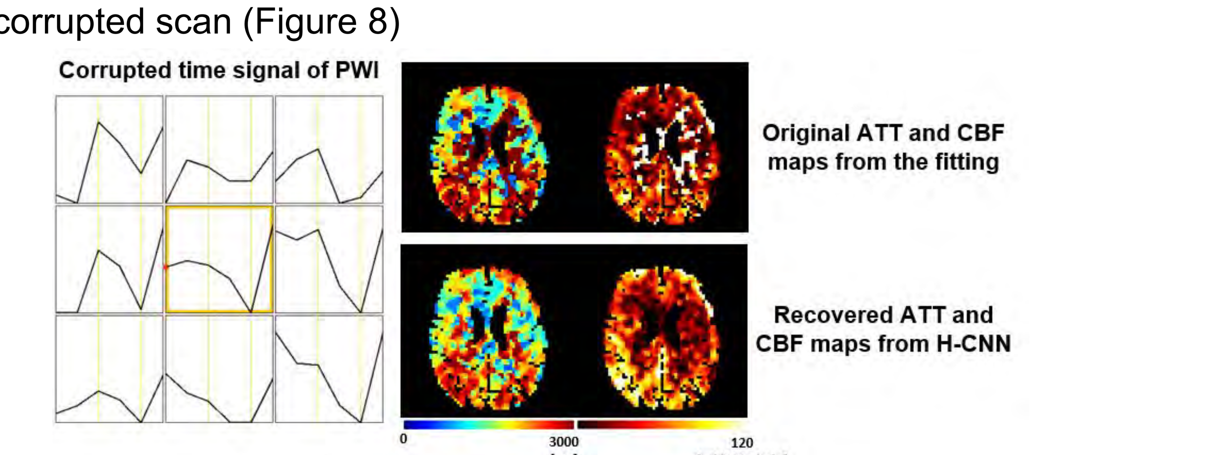

Figure 8. An example of recovering a corrupted scan

Acknowledgements

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References

[1] Buxton, Richard B., et al. *Magnetic resonance in medicine* 1998;40(3):383-396.
[2] Johnston, Megan E., et al. *IEEE transactions on medical imaging* 2015;34(6): 1392-1402.