Recurrent reconstruction network enables real-time and high-resolution PRF thermometry for LITT

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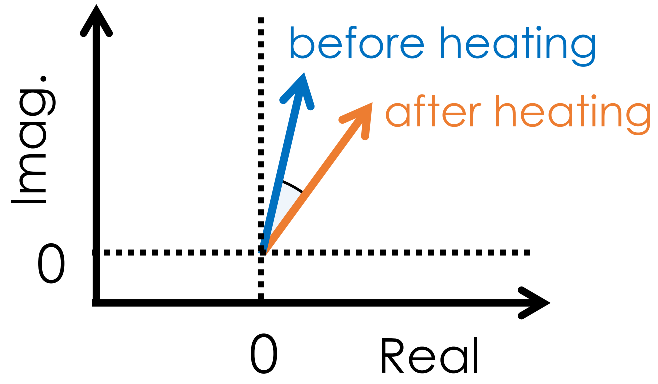
Introduction

$$\Delta\omega_0 = \boldsymbol{\alpha} \cdot \Delta T \cdot \gamma B_0$$



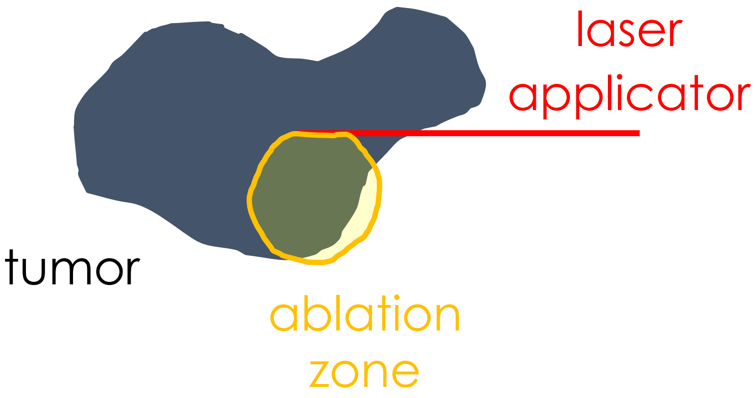
LITT is used for brain disease treatment, with **PRF shift-based thermometry** usually employed for temperature monitoring.

Recent LITT calls for PRF thermometry with:

- large volume coverage
- high spatiotemporal resolution
- real-time reconstruction

Needs acceleration!

conformable ablation



LITT: Laser interstitial thermal therapy, PRF: Proton resonance frequency

[1] Consales et al., Front Neurol, 2021. [2] Blackwell et al., JMRI, 2020. [3] Desclides M, et. Al., Proc. ISMRM, 2022

Introduction-Acceleration

Parallel Imaging

- Uniform undersampling.
- GRAPPA or SENSE for reconstruction.

Pros:

- simple implementation
- widely-used

Cons:

- limited acceleration factor

Improved acceleration

- Fast acquisition using CS, EPI, spiral, etc.
- Specialized reconstruction methods (AscLR, dTV, etc.)

Pros:

- high acceleration factor

Cons:

- low reconstruction speed

Deep learning

- Usually CS acquisition
- Deep learning reconstruction (CRNN, MoDL, etc.)

Pros:

- high acceleration factor
- high reconstruction speed

Cons:

- low generalizability

GRAPPA: GeneRalized Autocalibrating Partially Parallel Acquisitions, SENSE: sensitivity encoding, CS: compressed sensing, EPI: echo-planer imaging

[1] Wang et al., proc. ISMRM, 2016. [2] Chen et al., MRI, 2016. [3] Schlemper et al., TMI, 2018. [4] Qin et al., TMI, 2019. [5] Pan et al., Proc. ISMRM, 2022.

Methods-Overview

Acquisition

- 2D multi-echo GRE
- Compressed-Sensing (CS) Undersampling

Reconstruction

- Recurrent Reconstruction Network (RRN).
- RRN is trained on in vivo PRF data.

Experiments

- Retrospectively undersampling experiments.
- Prospectively undersampling experiments.

CS mask

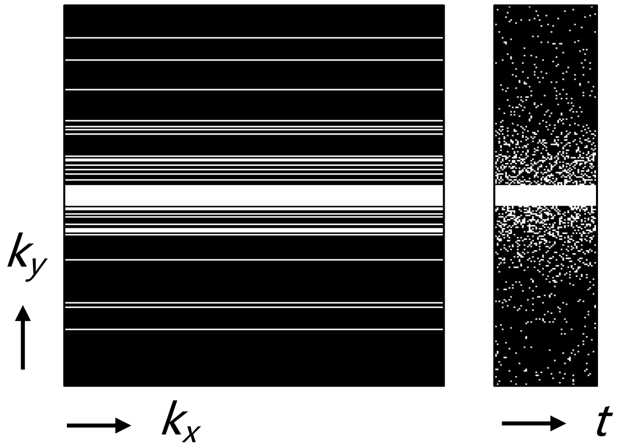
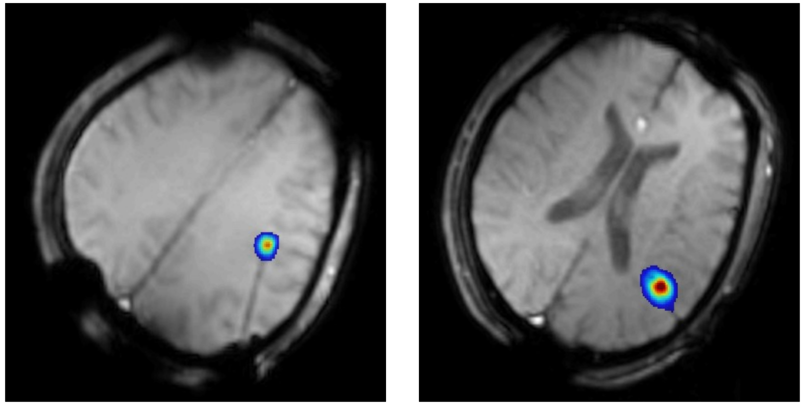
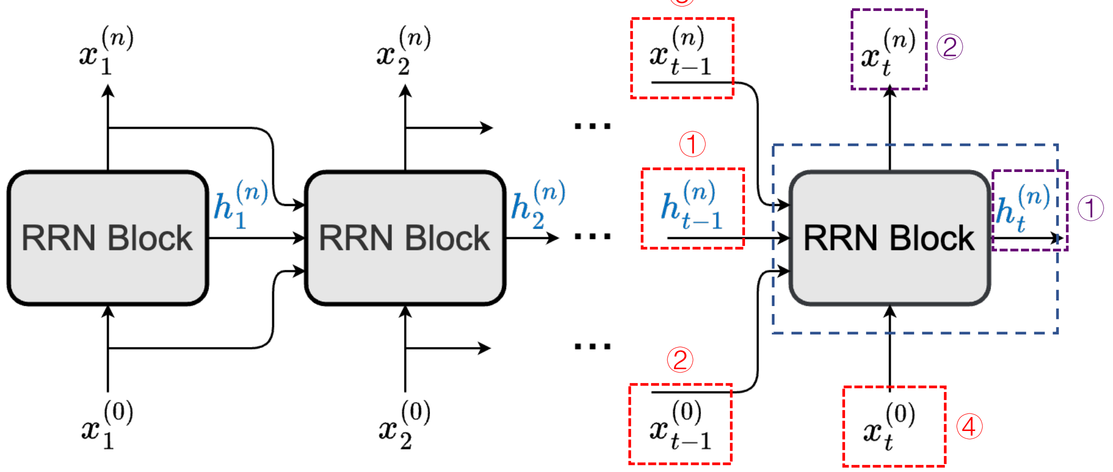


image example

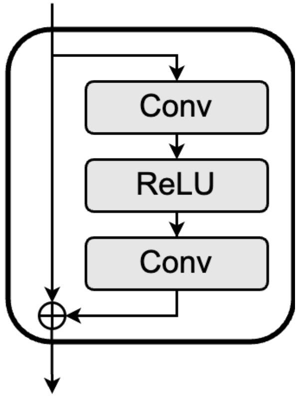


Methods-RRN

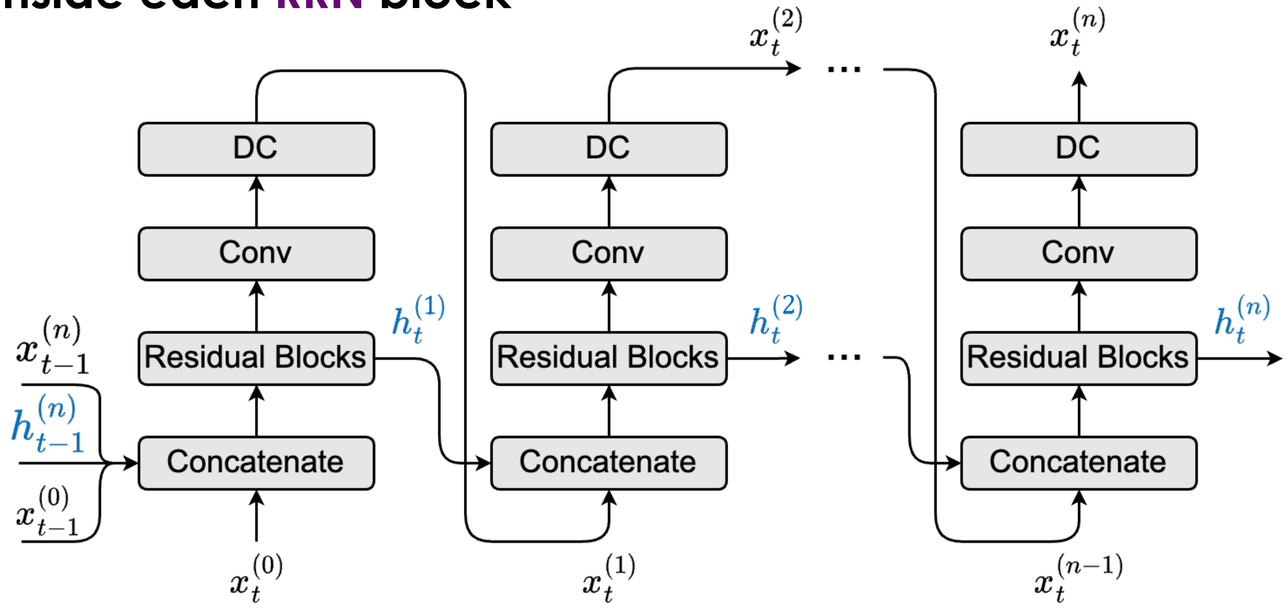
Network architecture



Residual Block:



Inside each RRN block



after iteration n

$h_t^{(n)}$: hidden feature

at frame t

$x_t^{(n)}$: reconstructed image

$*\ n = 0$ means zero-filled reconstruction

Methods-Data and experiments

Data acquisition

- PRF thermometry data from 18 patients during LITT.

Data set	Size
Training set	14
Validation set	1
Test set	3

Network training

- 8× CS-undersampled
- Reconstruction by RRN
- L2 loss

Retrospective experiments

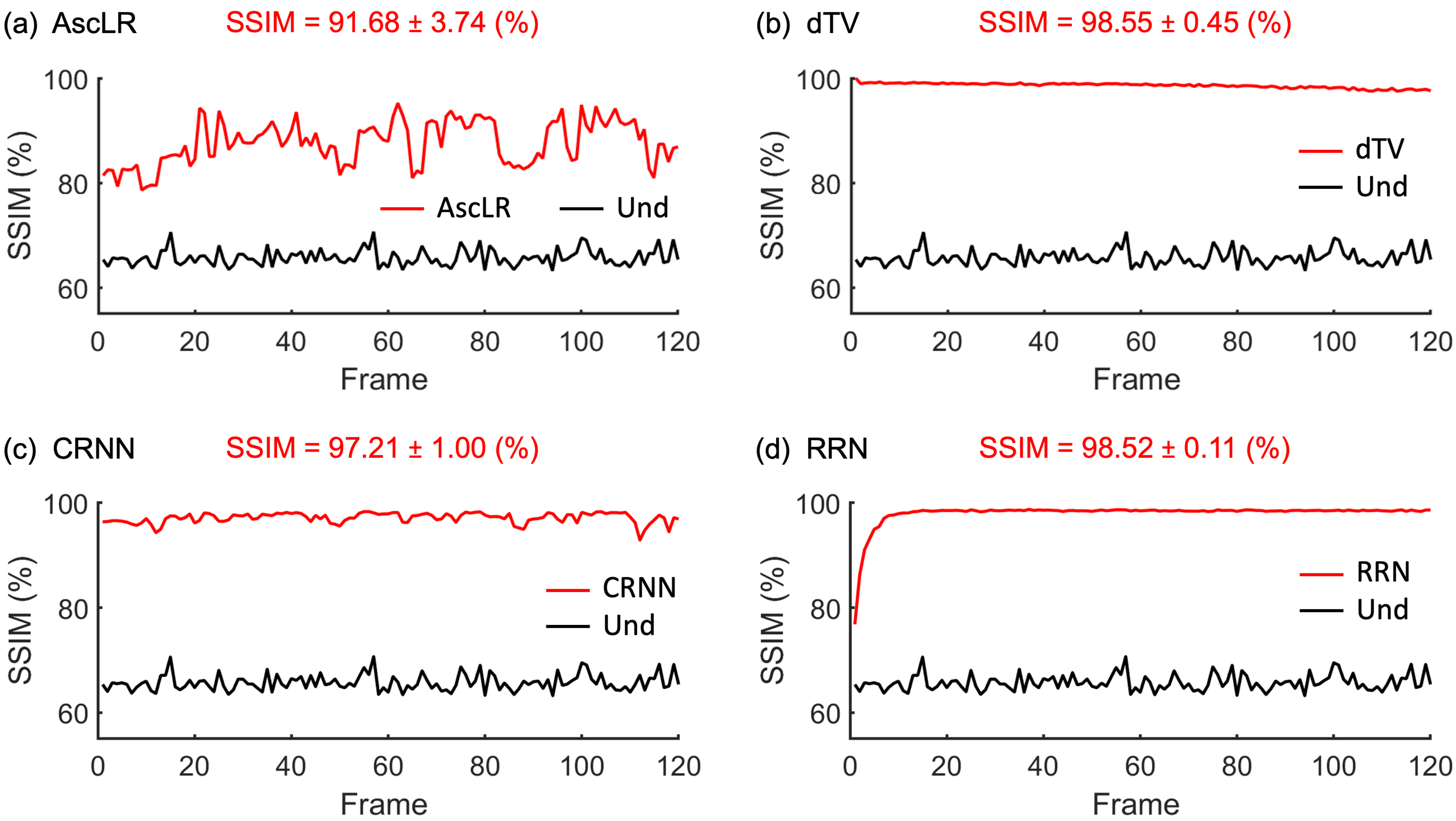
- Retrospectively 8× CS-undersampling on the test set.
- Reconstruction by AscLR, dTV, CRNN and RRN.

Prospective experiments

- Prospectively 8× CS-undersampling for MR acquisition during heating.
- Resolution = 1.8 mm isotropic, 12 slices, 4.8 s/frame.
- Optic sensor for temperature ground-truth.

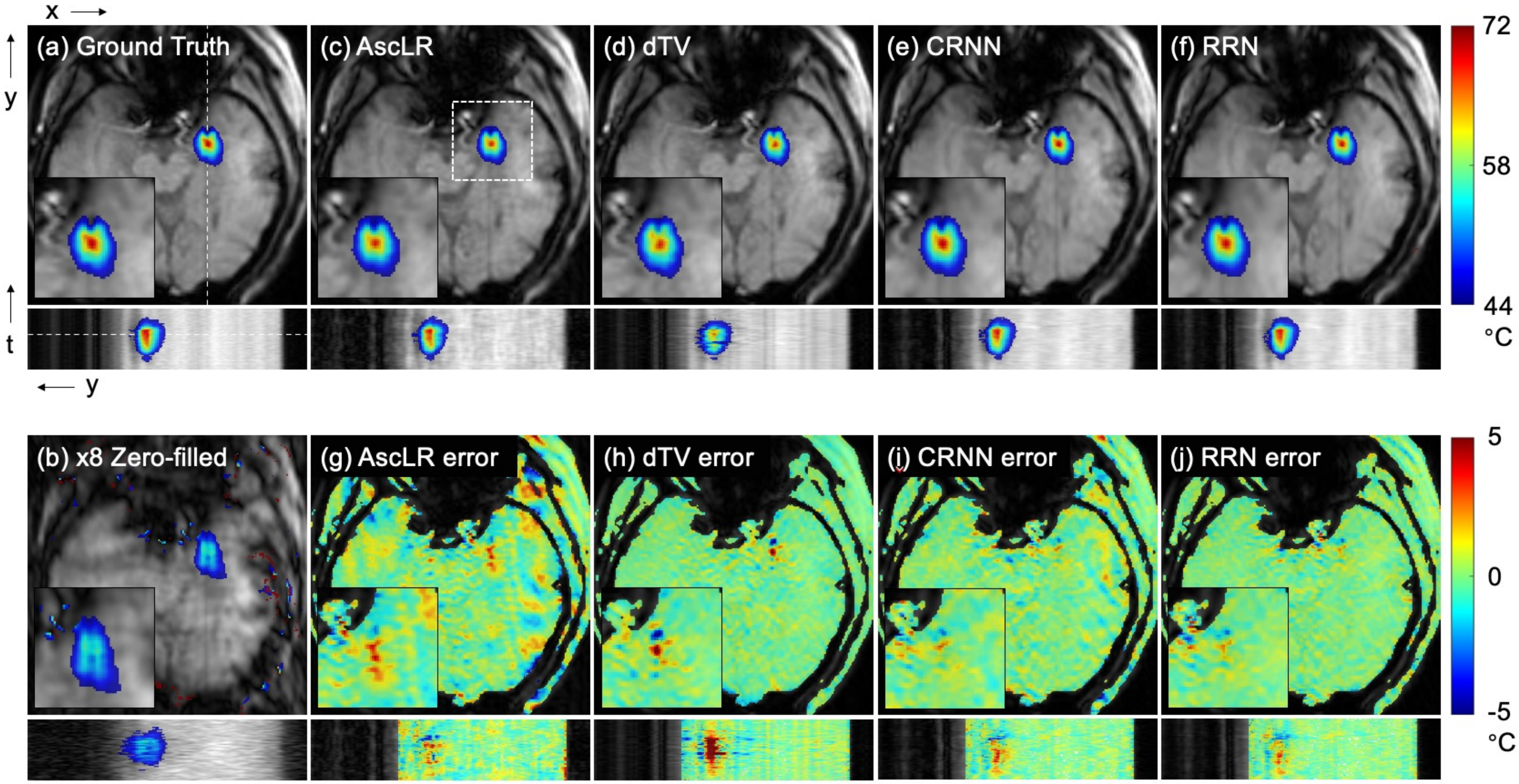
Results

Retrospective: Magnitude SSIM curve



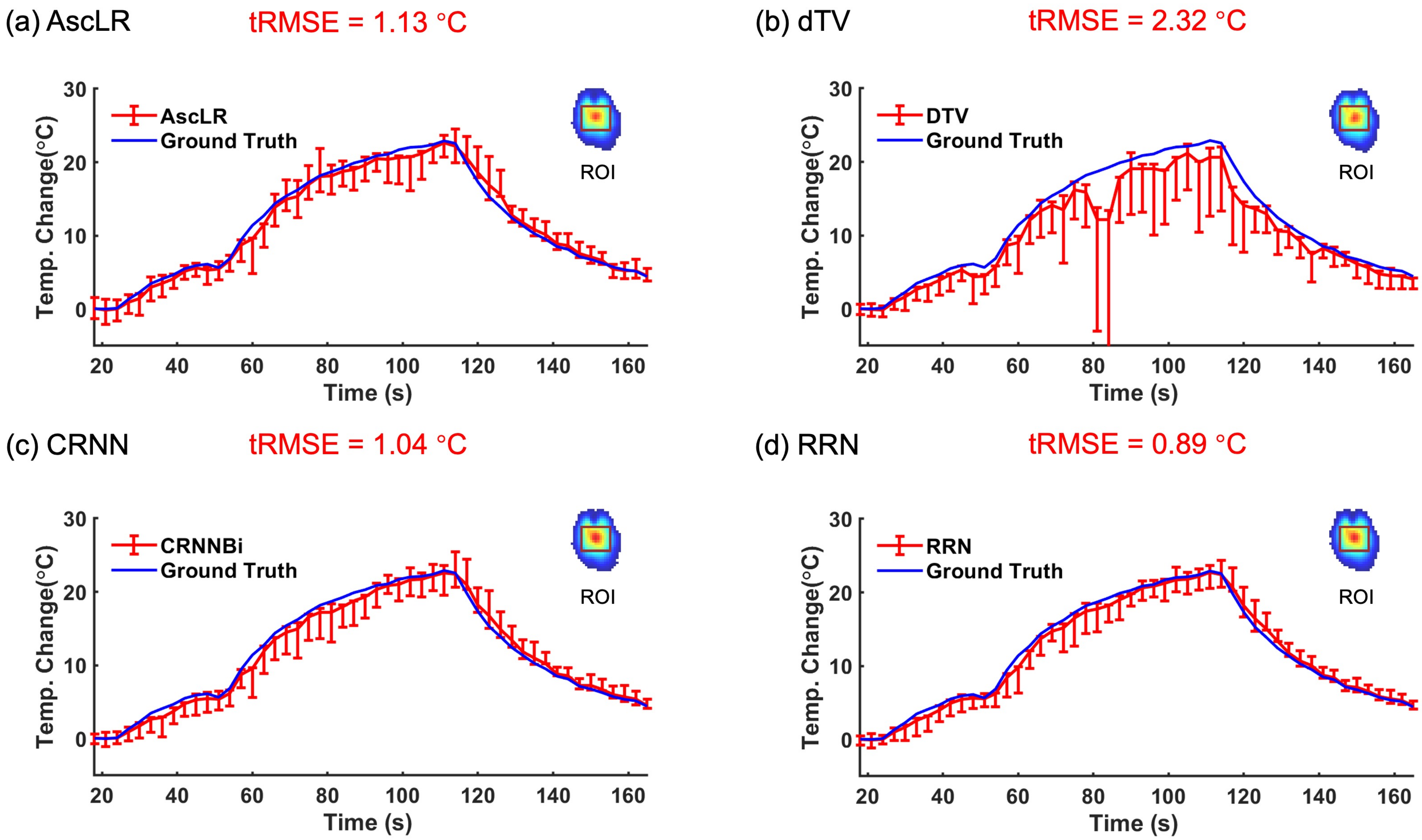
Results

Retrospective: Temperature reconstruction



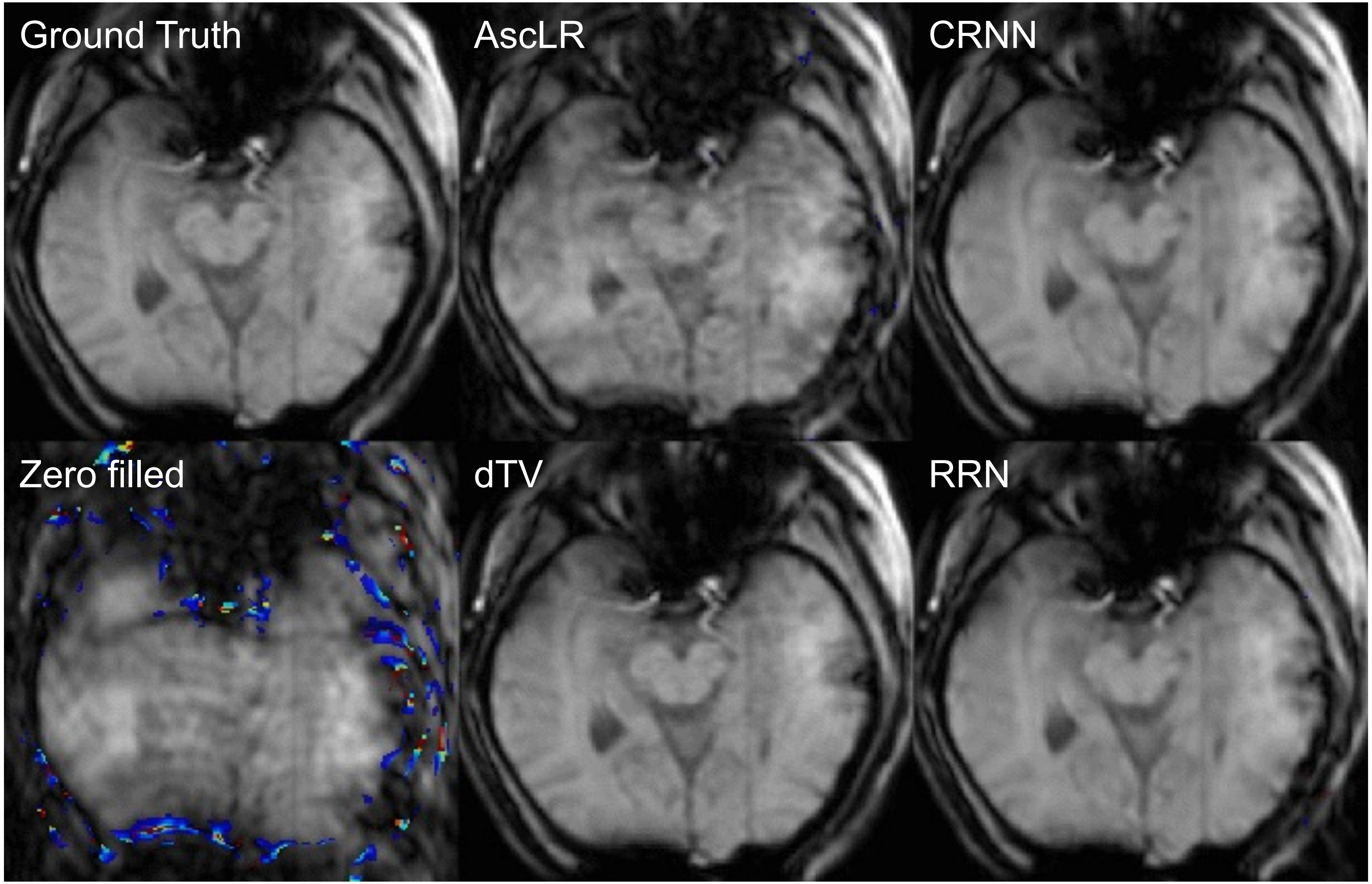
Results

Retrospective: Temperature reconstruction



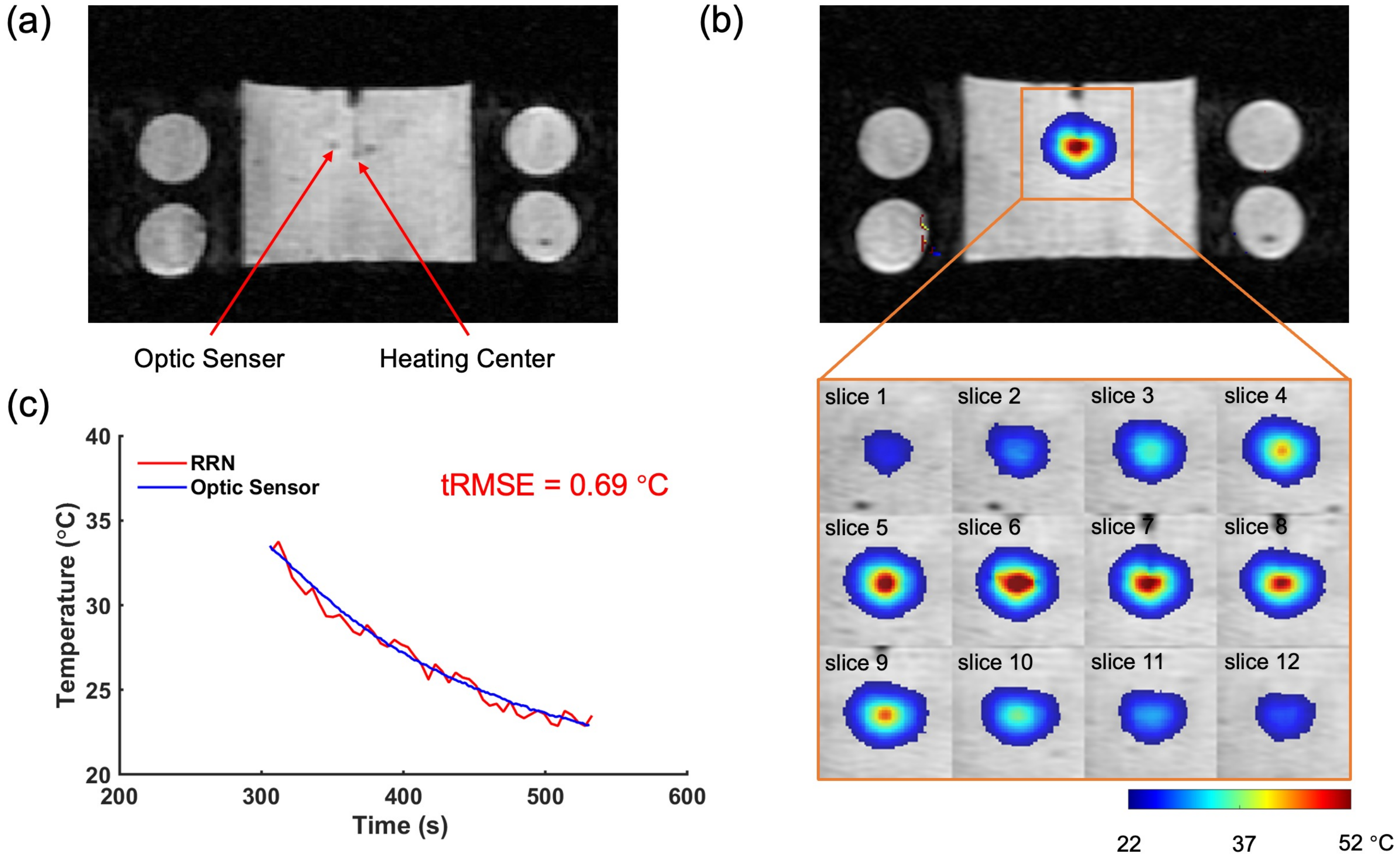
Results

Retrospective: Overall reconstruction



Results

Prospective: Temperature reconstruction



Discussion and Conclusion

We propose RRN for high-resolution, large-coverage, real-time MR thermometry.

RRN is effective in both retrospective and prospective experiments.

More prospective experiments need to be done in the future.

Acknowledgement