Deblurring for spiral real-time MRI using convolutional neural networks

Yongwan Lim, Shrikanth S. Narayanan, Krishna S. Nayak

Ming Hsieh Department of Electrical and Computer Engineering, Viterbi School of Engineering,

University of Southern California, Los Angeles, California, USA

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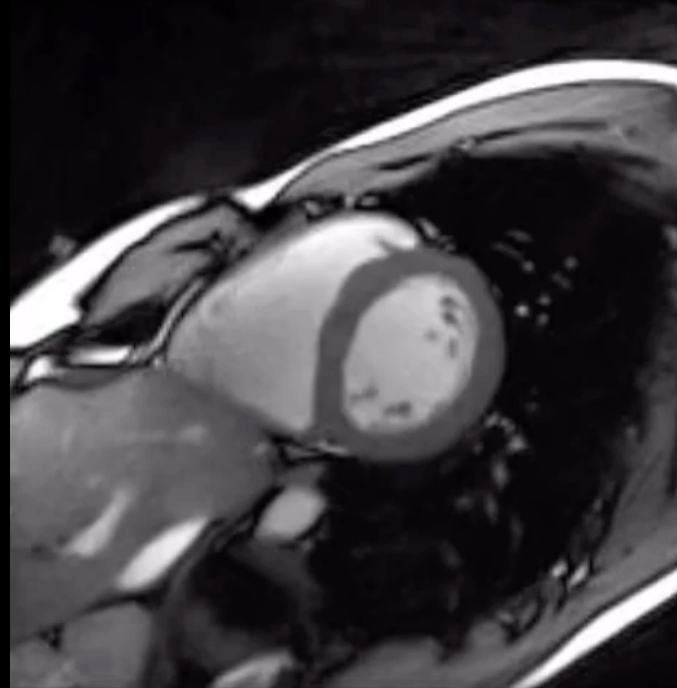
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Spiral Real-time MRI

Vocal Tract

Source: USC

Heart

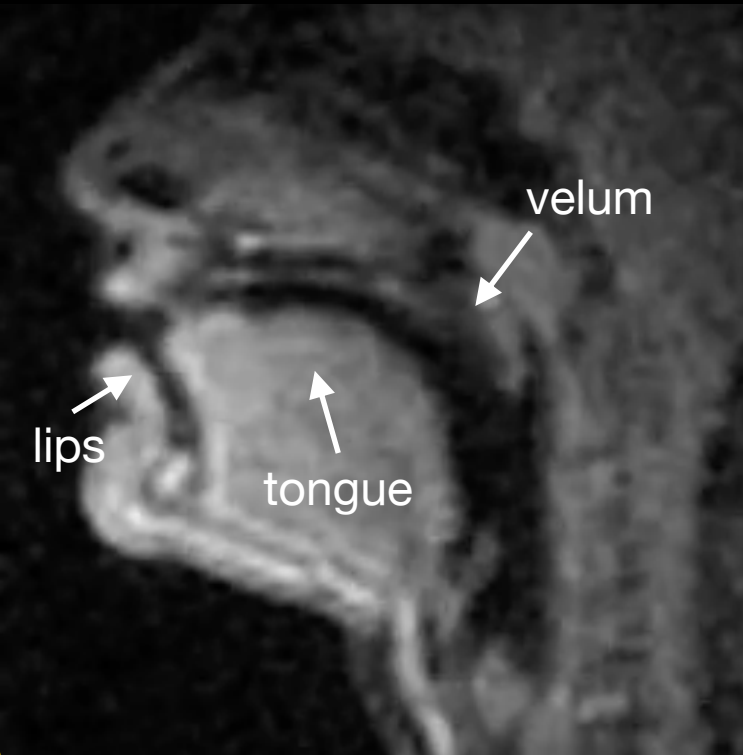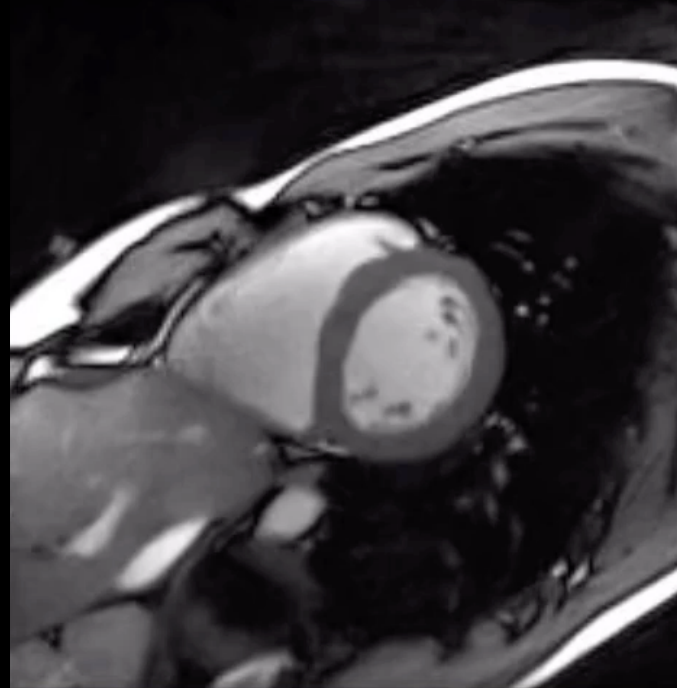Source: Max Plank BiomedNMR

Joints

Source: Chaudhari Lab, UC Davis

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velum

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Spiral Real-time MRI

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Spatially-varying blur due to spatial variations in the magnetic field

Spiral Real-time MRI

Vocal tract

lips

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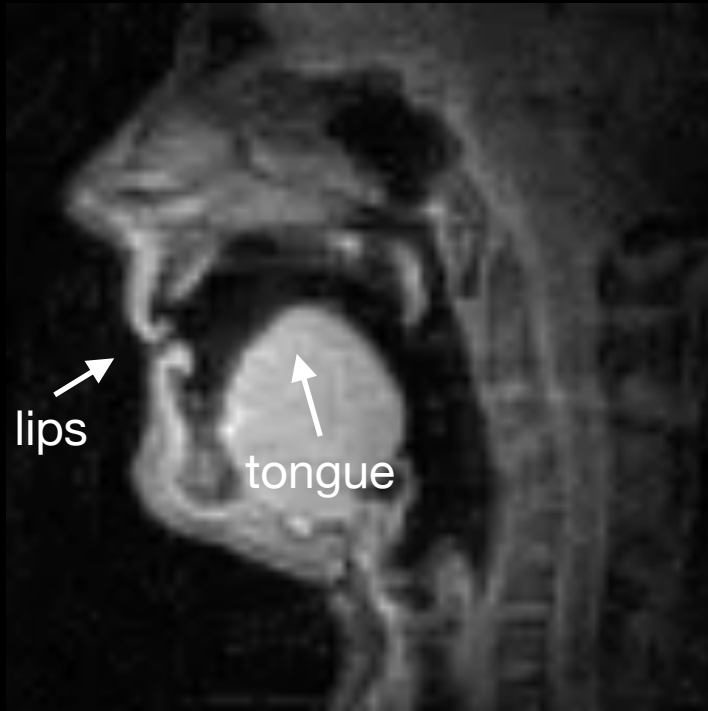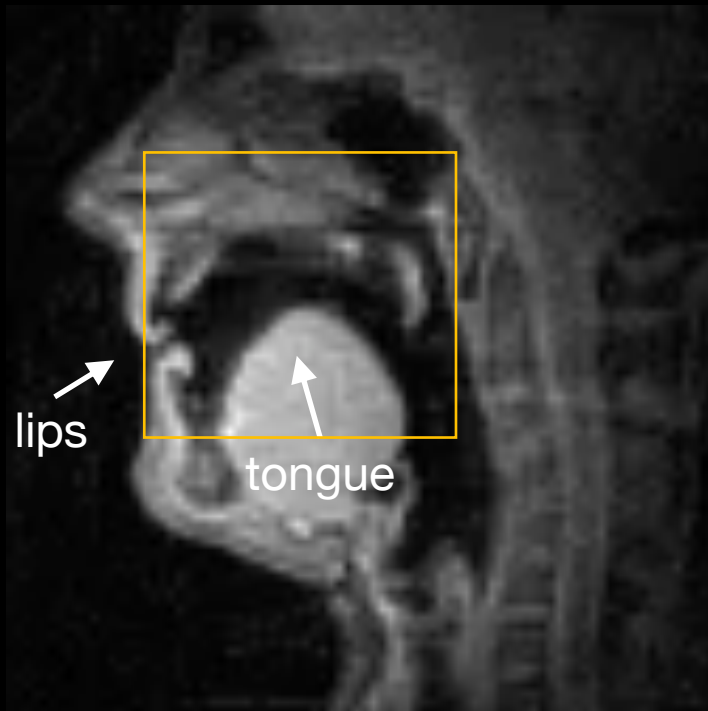
Source: USC

Spatially-varying blur **due to spatial variations in the magnetic field**
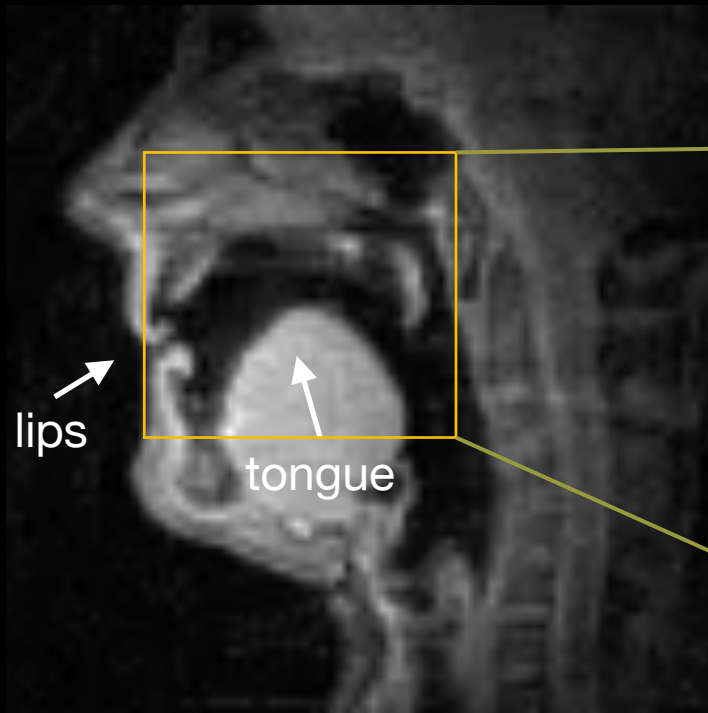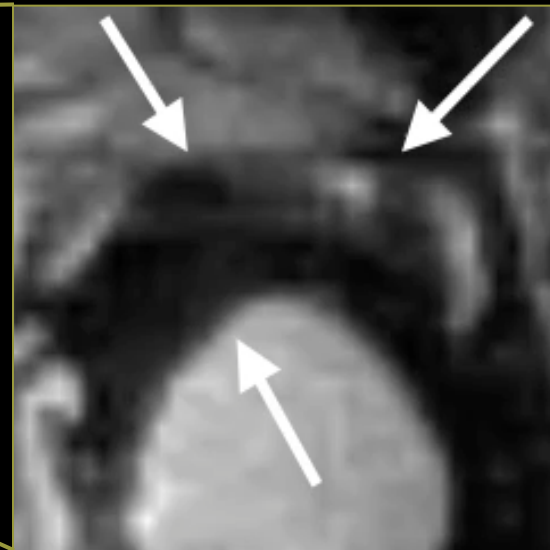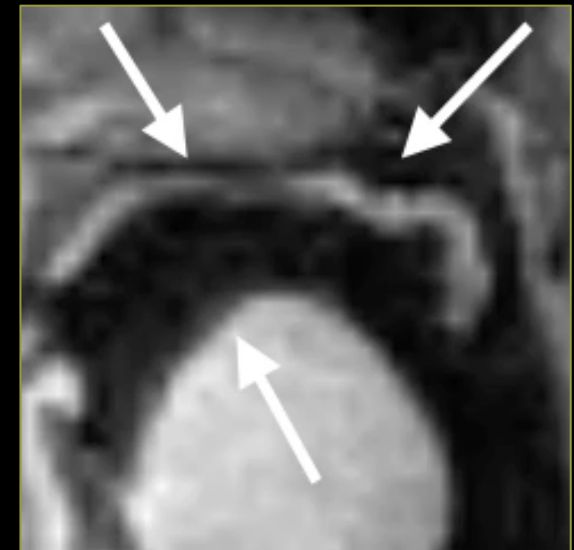
Off-resonance Deblurring

Blurry Image

Deblurred Image

1. KS Nayak et al, MRM. 2001   3. Y Lim et al. MRM. 2019
2. BP Sutton et al, JMRI. 2010   4. DC Noll et al, MRM. 1992

Off-resonance Deblurring

Blurry Image   Field Map

Deblurred Image

1. Field map acquisition
   - Reduced scan efficiency
2. Spatially-varying deconvolution
   - Computationally slow (~minutes)

1. KS Nayak et al, MRM. 2001   3. Y Lim et al. MRM. 2019
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Off-resonance Deblurring

Blurry Image   **Field Map**   **Deblurred Image**

Deconvolution

1. Field map acquisition
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Off-resonance Deblurring

- Standard Approaches[1-4]:

Blurry Image   Field Map   Deblurred Image

Deconvolution →

1. Field map acquisition
   - Reduced scan efficiency
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- Proposed Approach: A supervised end-to-end learning

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Off-resonance Deblurring
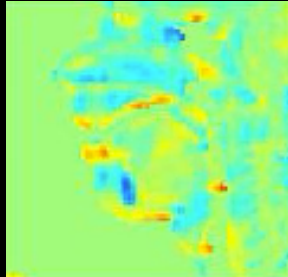
- Standard Approaches[1-4]:

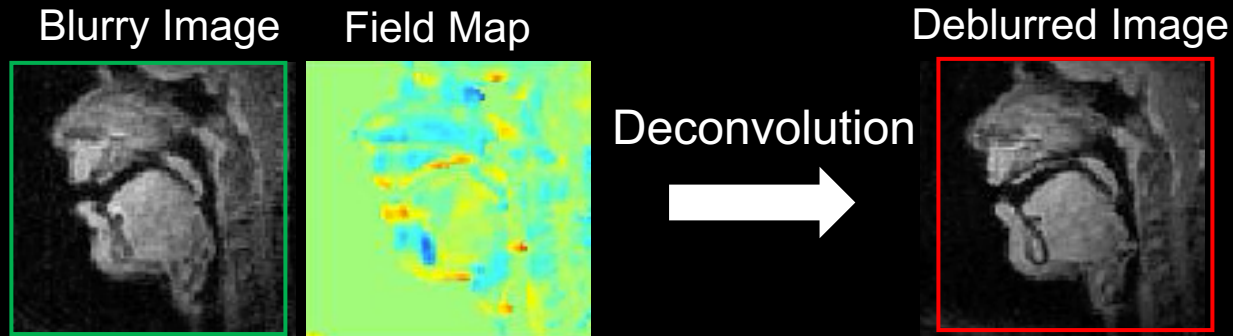Blurry Image   Field Map   Deblurred Image

Deconvolution

1. Field map acquisition
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2. Spatially-varying deconvolution
   - Computationally slow (~minutes)

- Proposed Approach: A supervised end-to-end learning

Convolutional
Neural Networks

conv2D   conv2D   conv2D
ReLU   tanh   tanh

Skipped connection

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Off-resonance Deblurring

- Standard Approaches[1-4]:

Blurry Image   Field Map   Deblurred Image

Deconvolution
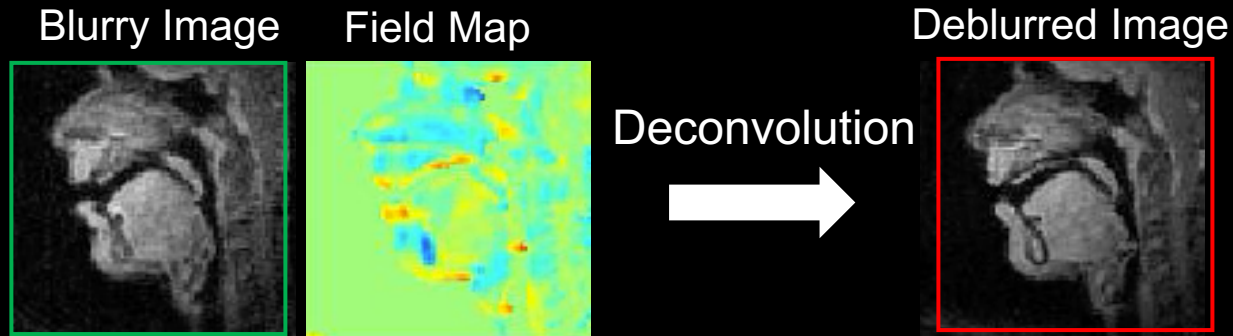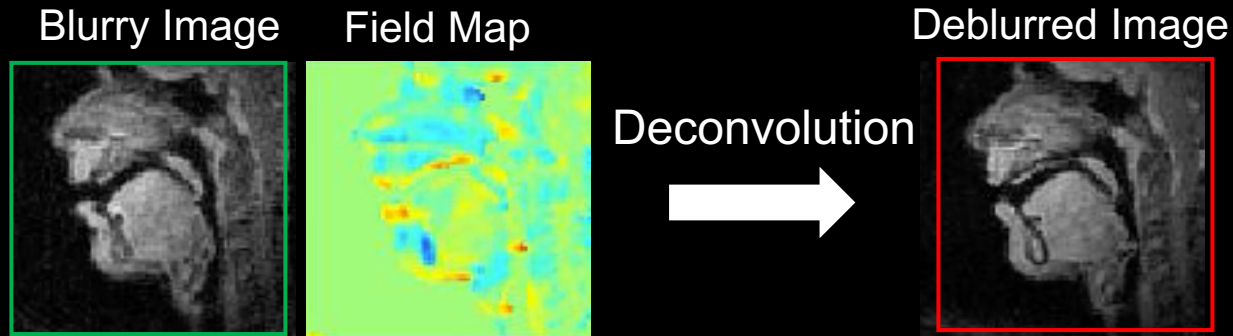
1. Field map acquisition
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- Proposed Approach: A supervised end-to-end learning

Blurred Image   Convolutional Neural Networks   Deblurred Image

conv2D ReLU   conv2D tanh   conv2D tanh

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Off-resonance Deblurring

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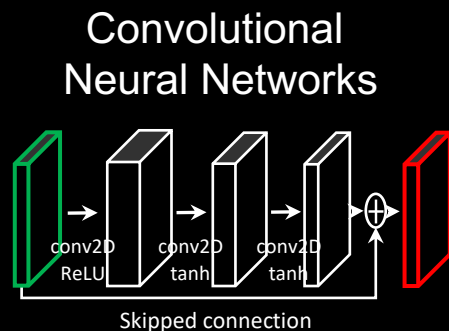
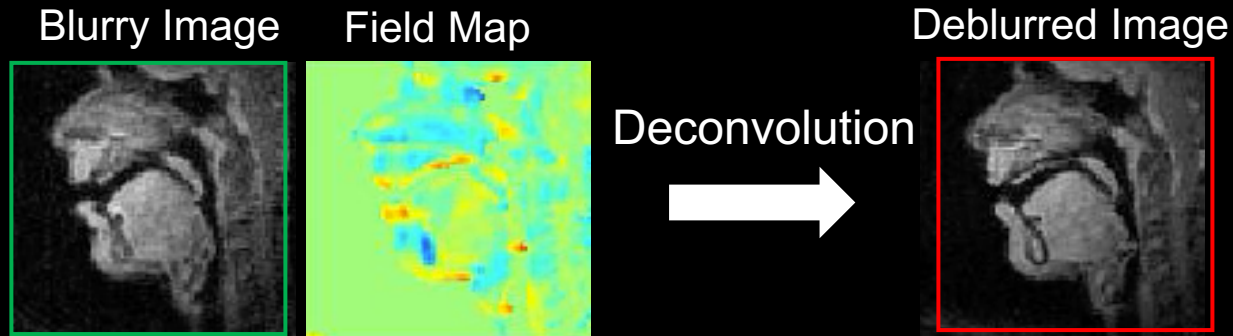- Proposed Approach: A supervised end-to-end learning

Blurred Image   Convolutional Neural Networks   Deblurred Image

conv2D ReLU   conv2D tanh   conv2D tanh

Skipped connection

In test time
1. Does NOT rely on field map
2. FAST (~milliseconds)

1. KS Nayak et al, MRM. 2001
2. BP Sutton et al, JMRI. 2010
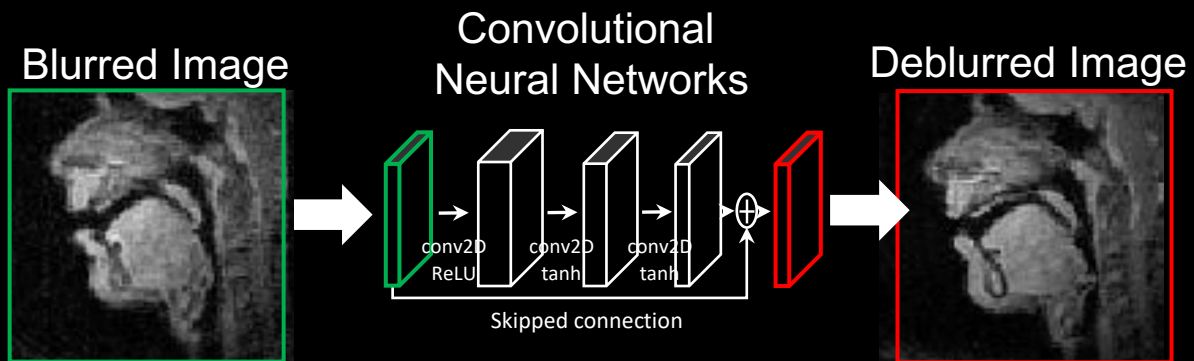3. Y Lim et al. MRM. 2019
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Off-resonance Deblurring

- Standard Approaches[1-4]:

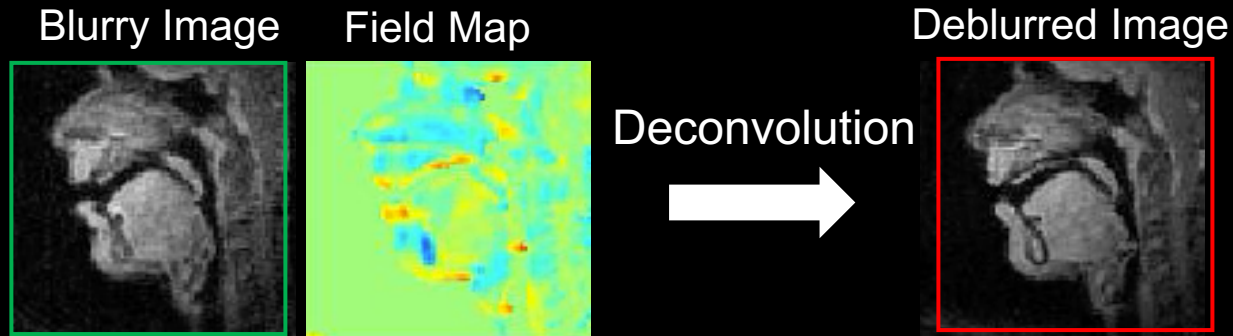Blurry Image   Field Map   Deblurred Image

Deconvolution

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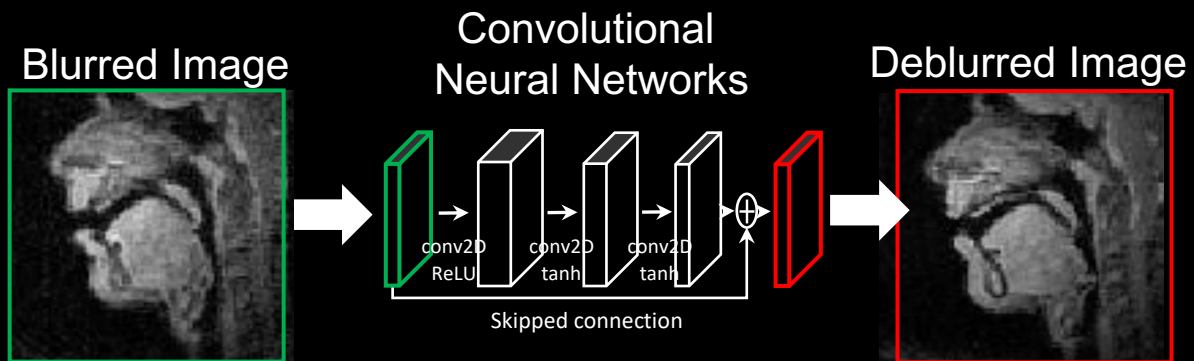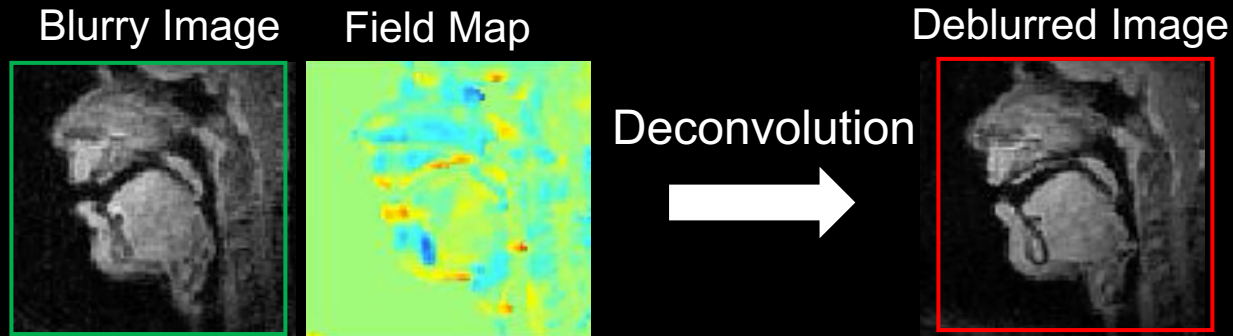- Proposed Approach: A supervised end-to-end learning

Blurred Image   Convolutional Neural Networks   Deblurred Image

conv2D ReLU   conv2D tanh   conv2D tanh

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Proposed Supervised Deblurring

Field Map   **Ground Truth**

Deblur residual blurring
using a previous method[1]

Simulate blurring
based on MRI physics and
data augmentation[2]

Train CNNs

1. Y Lim et al. MRM. 2019
2. Y Lim et al. MRM. 2020

Proposed Supervised Deblurring

Field Map

Ground Truth

Synthetically Blurred Image

Off-resonance Simulation

23 subjects
> 64K frames

Parameters:
T_{read}, α, β

Deblur residual blurring using a previous method[1]

Simulate blurring based on MRI physics and data augmentation[2]

Train CNNs

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Proposed Supervised Deblurring

Ground Truth
Synthetically Blurred Image

Training

23 subjects
> 64K frames

Parameters:
T_{read}, α, β

Convolutional
Neural Networks

conv2D
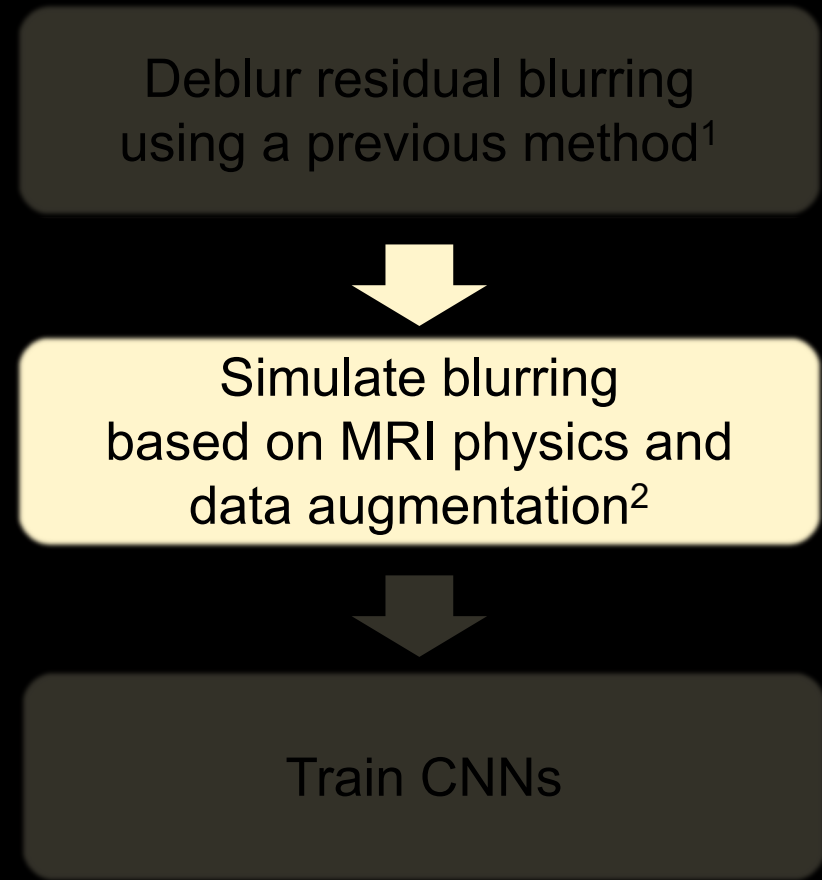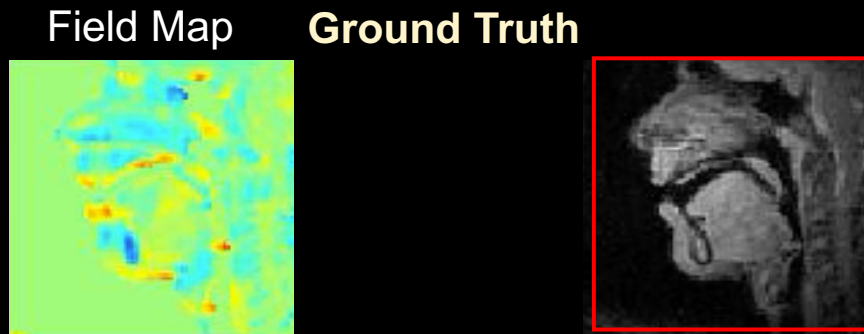ReLU
conv2D
tanh
conv2D
tanh

Skipped connection

Deblur residual blurring
using a previous method[1]

Simulate blurring
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Proposed Supervised Deblurring

Ground Truth | Synthetically Blurred Image

Training

23 subjects
> 64K frames

Parameters:
T_{read}, α, β

Inference

Blurred Image

Convolutional Neural Networks
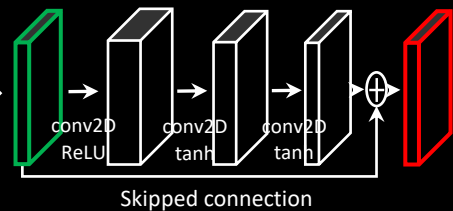
Deblurred Image

conv2D ReLU
conv2D tanh
conv2D tanh
Skipped connection

Deblur residual blurring using a previous method[1]

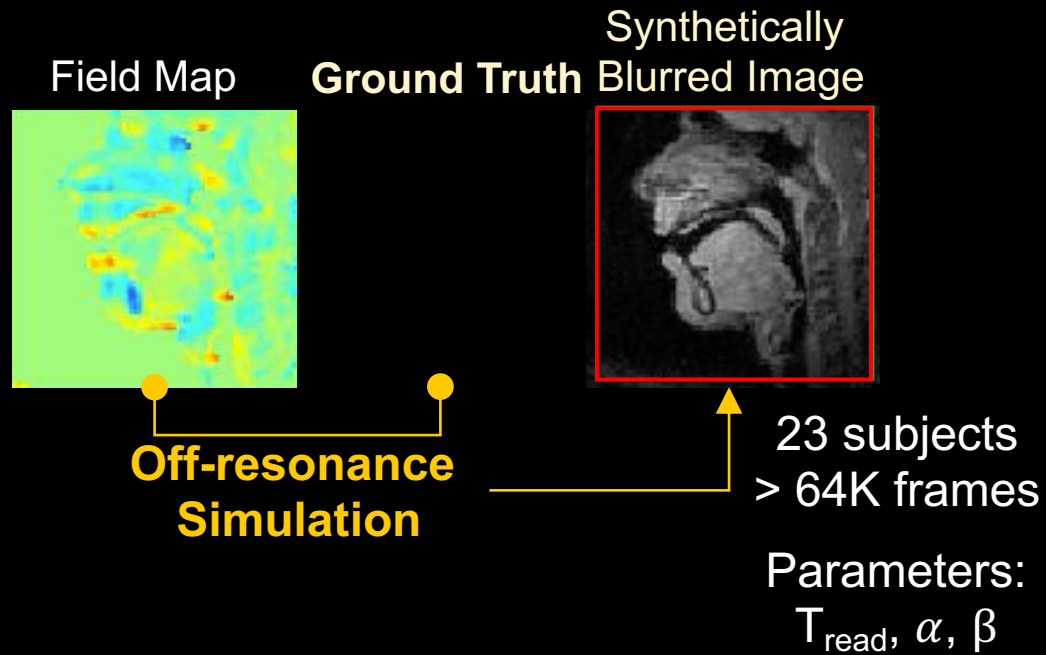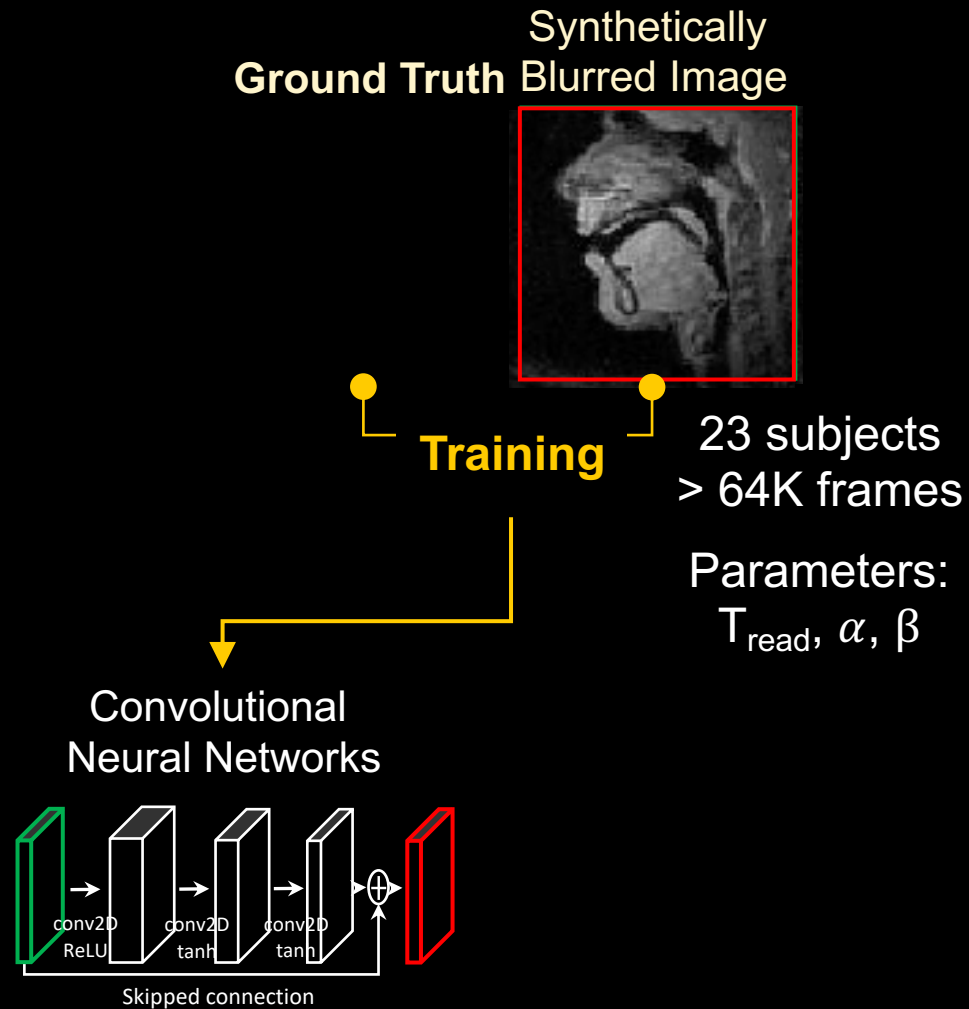Simulate blurring based on MRI physics and data augmentation[2]

Train CNNs

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Result: Synthetic Test Data

Ground truth   **Uncorrected**

Image

- lips
- soft palate
- tongue
- y
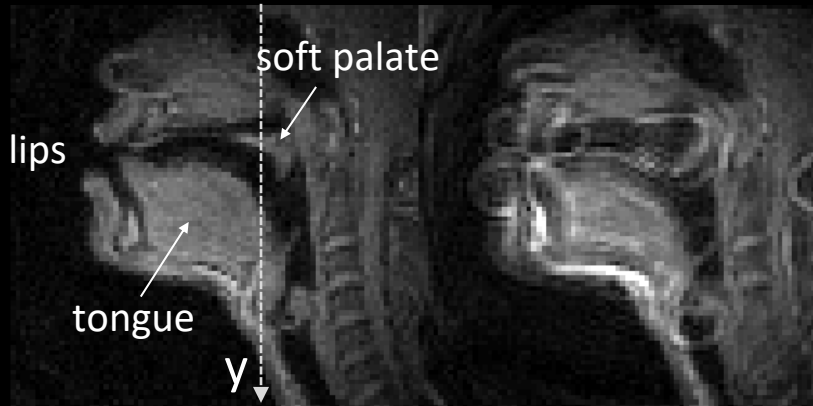
PSNR	22.16 ± 1.413
SSIM	0.812 ± 0.039
HFEN	0.568 ± 0.131

1. LC Man et al. MRM. 1997   2. BP Sutton et al. MRM. 2003

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Result: Synthetic Test Data

	Ground truth	Uncorrected	MFI[1] with ref. field map	IR[2] with ref. field map	Proposed
PSNR		22.16 ± 1.413	20.75 ± 1.363	$\mathbf{38.53} \pm 1.259$	29.30 ± 1.762
SSIM		0.812 ± 0.039	0.875 ± 0.023	$\mathbf{0.992} \pm 0.002$	0.944 ± 0.016
HFEN		0.568 ± 0.131	0.448 ± 0.113	$\mathbf{0.004} \pm 0.003$	0.088 ± 0.049

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Result: Synthetic Test Data

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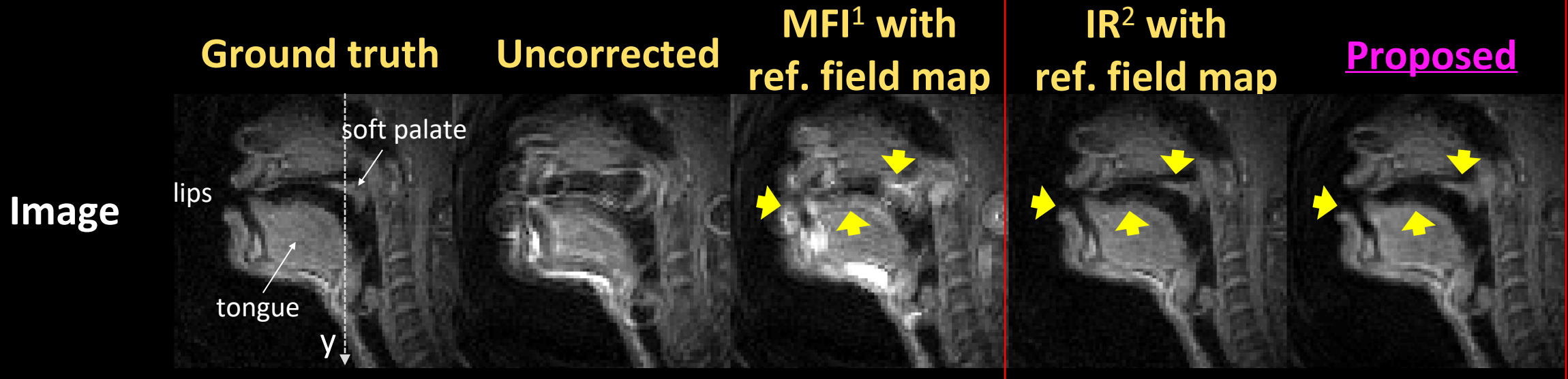
Result: Real Test Data

Uncorrected   **IR with estimated field map[1]**   **Proposed**

Readout = 7.94 ms

Temporal resolution = 46 ms

1. Y Lim et al. MRM. 2019

Summary

- We develop a CNN-based deblurring method for spiral RT-MRI in speech production.

- It is field-map-free and effective at resolving spatially varying blur at the articulator boundaries.

- It is extremely fast (12.3 ms per-frame) with negligible impact on latency or workflow for RT-MRI applications.

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University of Southern California, Los Angeles, California, USA

Thank you for your attention!

If you have any questions, please contact me: yongwanl@usc.edu