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# Convolutional neural network-based reverse time migration with multiple energy

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December 2, 2021
CREWES 2021 Sponsor Meeting

NSERC CRSNG
UNIVERSITY OF CALGARY
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# Outline

- Motivation
- Theory
- Numerical examples
- Conclusion and future work

# Motivation

Reverse time migration

Handle steep geologic structure and lateral velocity variations

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1. Mitigate the artifacts
2. Improve the resolution
3. Learn the lithologic structure from different feature maps

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Aperture limited

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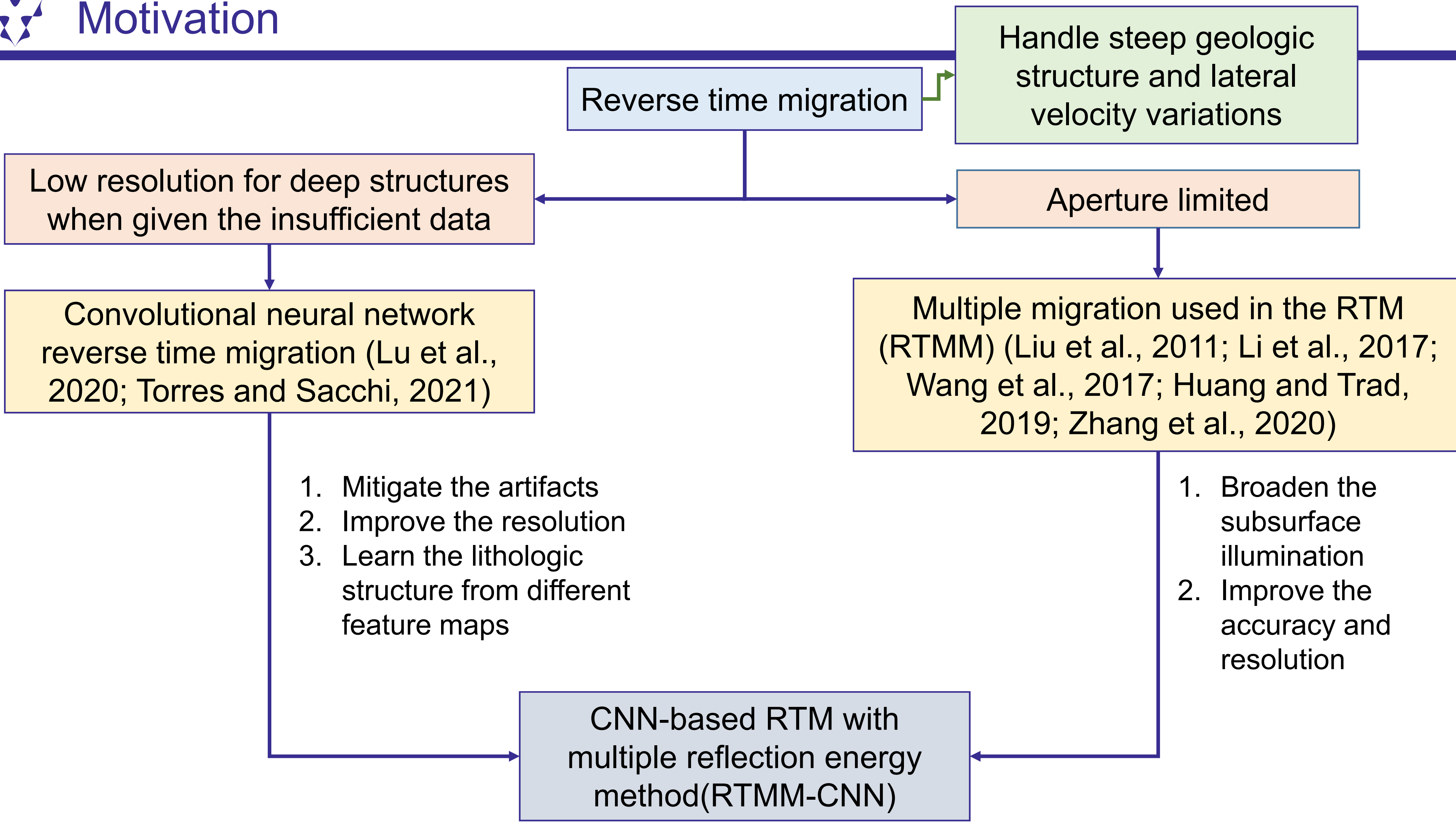
Multiple migration used in the RTM (RTMM) (Liu et al., 2011; Li et al., 2017; Wang et al., 2017; Huang and Trad, 2019; Zhang et al., 2020)

1. Broaden the subsurface illumination
2. Improve the accuracy and resolution

# Motivation


Reverse time migration
Handle steep geologic structure and lateral velocity variations
Low resolution for deep structures when given the insufficient data
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3. Learn the lithologic structure from different feature maps
1. Broaden the subsurface illumination
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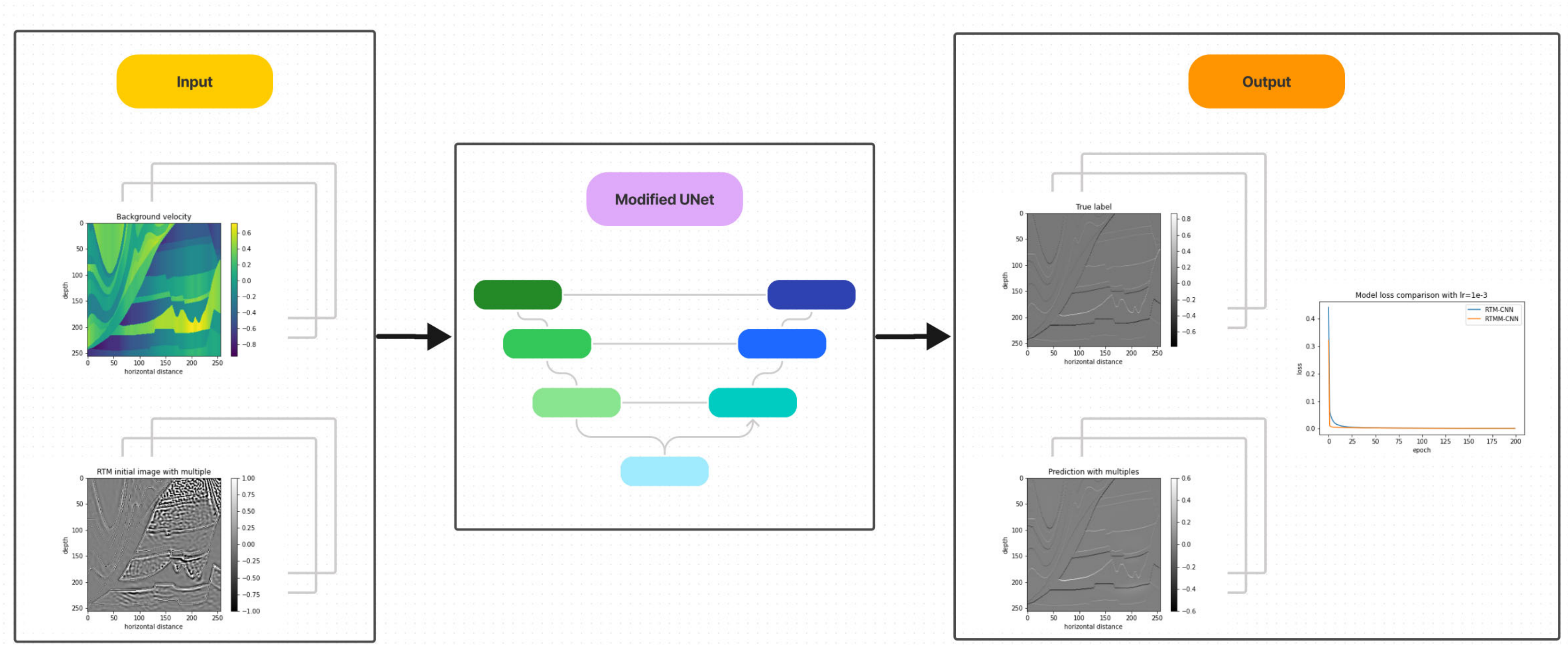
CNN-based RTM with multiple reflection energy method(RTMM-CNN)

# Theory

- RTM with surface multiple (RTMM)
- A modified U-Net based RTM with multiple (RTMM-CNN)



# RTM with surface multiple (RTMM)

- Based on the modified RTM scheme with multiple reflections (Liu et al., 2011), we only use the primary and first-order multiple reflections.

Observed data: $\mathbf{U}(z_0, z_0) = \mathbf{X}\,\mathbf{S}(z_0, z_0)$ (1)

Observed data after free surface reflection: $\mathbf{D}(z_0, z_0) = -\mathbf{U}(z_0, z_0)$ (2)

where
$\mathbf{S}(z_0, z_0)$: the source
$\mathbf{X}$: the media response matrix

First-order multiple: $\mathbf{M}(z_0, z_0) = -\mathbf{X}\,\mathbf{D}(z_0, z_0)$ (3)

The imaging condition:

$$\mathbf{I}(x, z) = \sum_{t=1}^{t_{max}} \mathbf{D}(x, z, t) * \mathbf{M_B}(x, z, t) \tag{4}$$

$$\mathbf{D}(x, z, t) = \mathbf{D}_P(x, z, t) + \mathbf{D}_M(x, z, t) \tag{5}$$

# A modified U-Net based RTM with surface multiple (RTMM-CNN)

- The network operator acts similar as the least-squares reverse time migration.
- For LSRTM, the solution is derived from the minimum difference between true and migrated images. The formal solution is:

$$\mathbf{m}^* = \boldsymbol{\Gamma}^{-1}\mathbf{m}_{mig} = \boldsymbol{\Gamma}^{-1}(\mathbf{L}^{\mathrm{T}}\mathbf{d}) \qquad (6)$$

$\boldsymbol{\Gamma}^{-1}$: the inverse Hessian

$\mathbf{m}_{mig}$: the migrated image

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$\mathbf{m}_{mig}$: the migrated image

- Similarly, based on Ronneberger et al. (2015), this modified U-Net can be used as an alternative way of inverse Hessian to determine the imaging result.

$$\mathbf{m}_{pred} = \mathbf{\Gamma}_{unet}(\mathbf{m}_{rtmm}, \mathbf{m}_{vel}) \qquad (7)$$

$\mathbf{\Gamma}_{unet}$: the multilayer CNN and skip connections

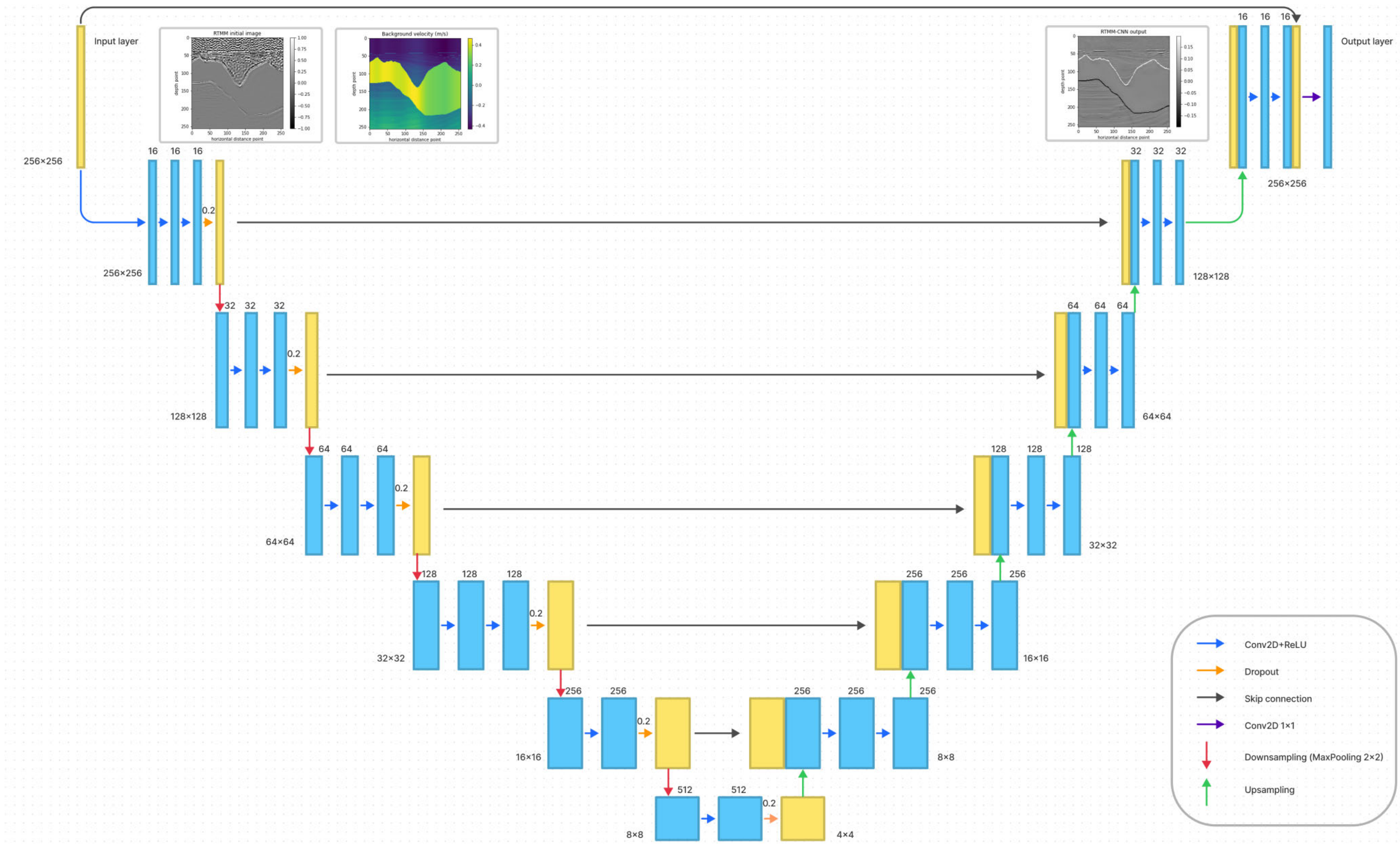
$\mathbf{m}_{rtmm}$: the RTMM initial image

$\mathbf{m}_{vel}$ is the background velocity

- The mean squared error (MSE) loss:

$$\mathrm{MSE} = \frac{1}{n}\sum_{i=1}^{n} ||\mathbf{m}_{pred}^{i} - \mathbf{m}_{true}^{i}||_2^2 \qquad (8)$$

# Modified U-Net



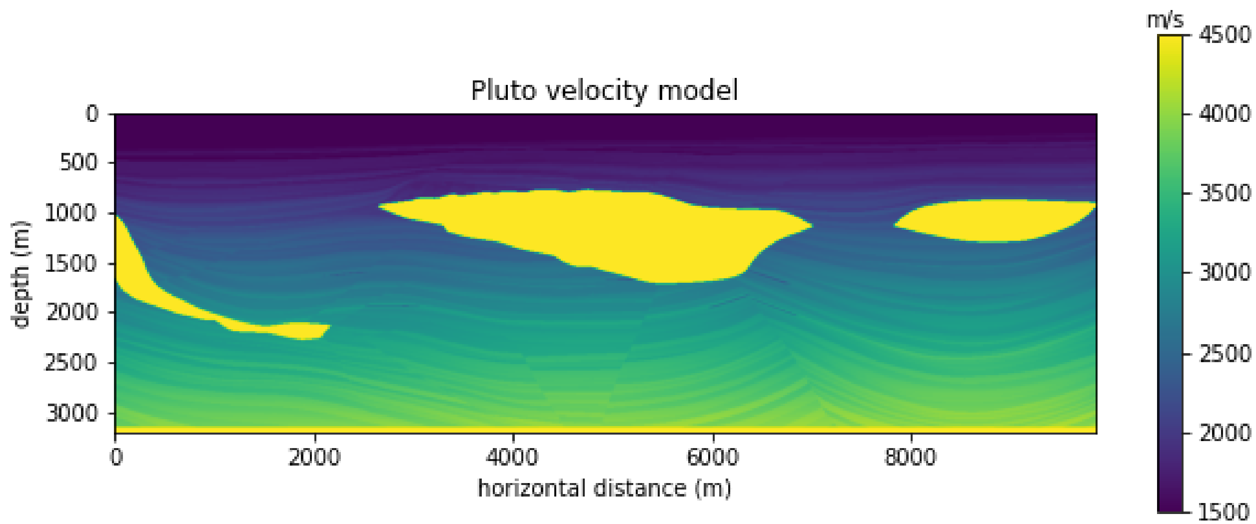
# Train and test set

- Sigsbee2b, Amoco, Agbami, Pluto, BP2004 and Marmousi as the origin input set
- A fourth-order finite difference method is used for the forward modeling
- Baseline model: RTM-CNN
- Before training, the whole RTM and RTMM images are partly chosen and divided randomly into 2100 spatial windows with 256x256 points
- The ratio of train and test set is 0.8: 0.2
- All the output predictions have normalized scaling

# Numerical examples

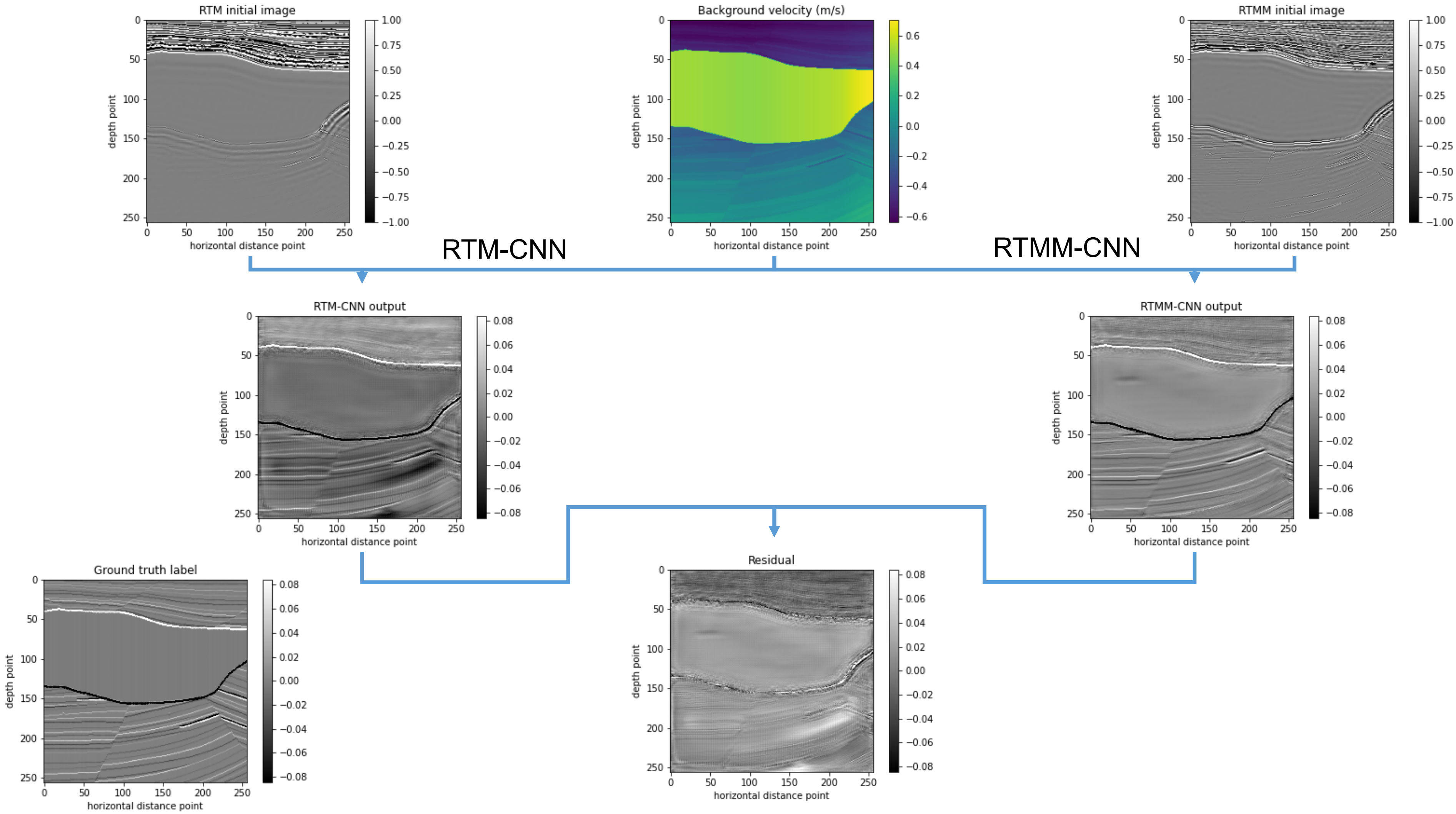
- Pluto model
- Marmousi model
- Foothill model (not used as our training or testing data)

# Numerical Example 1 – Pluto Model



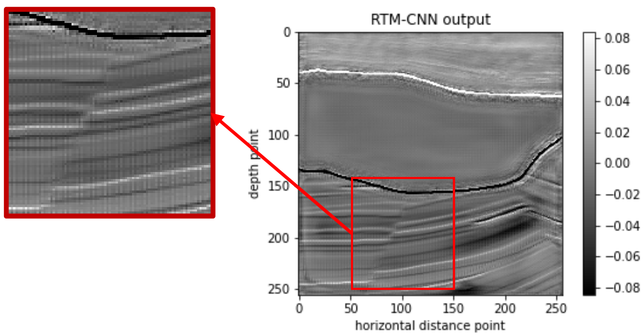

- 1234x401 gridpoints
- dx = dz = 8 meters
- t = 7.2 seconds with dt = 0.8 milliseconds
- ds = 80 meters, dg = 16 meters; ns = 122, ng = 615

# Numerical Example 1 – Pluto Model

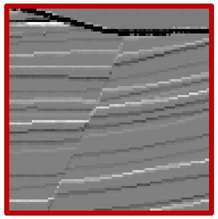


# Numerical Example 1 – Pluto Model

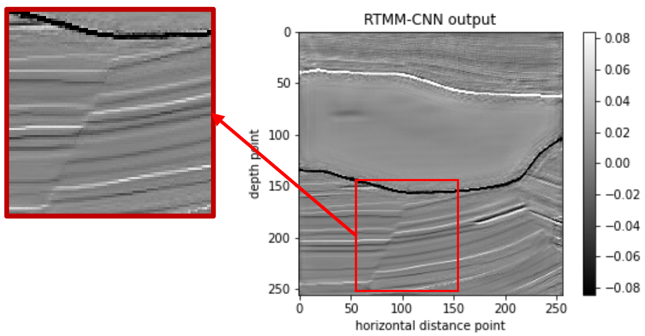
RTM-CNN




True Label

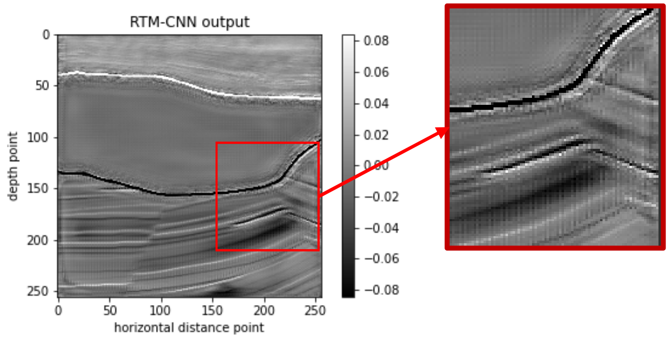


RTMM-CNN

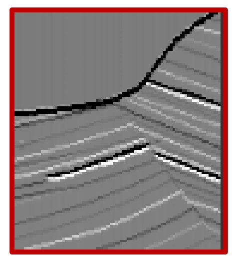


# Numerical Example 1 – Pluto Model

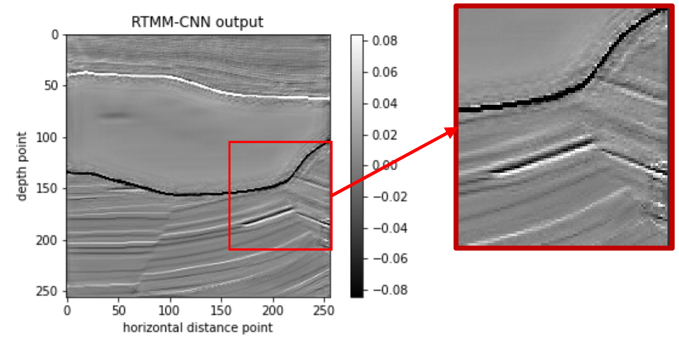
RTM-CNN



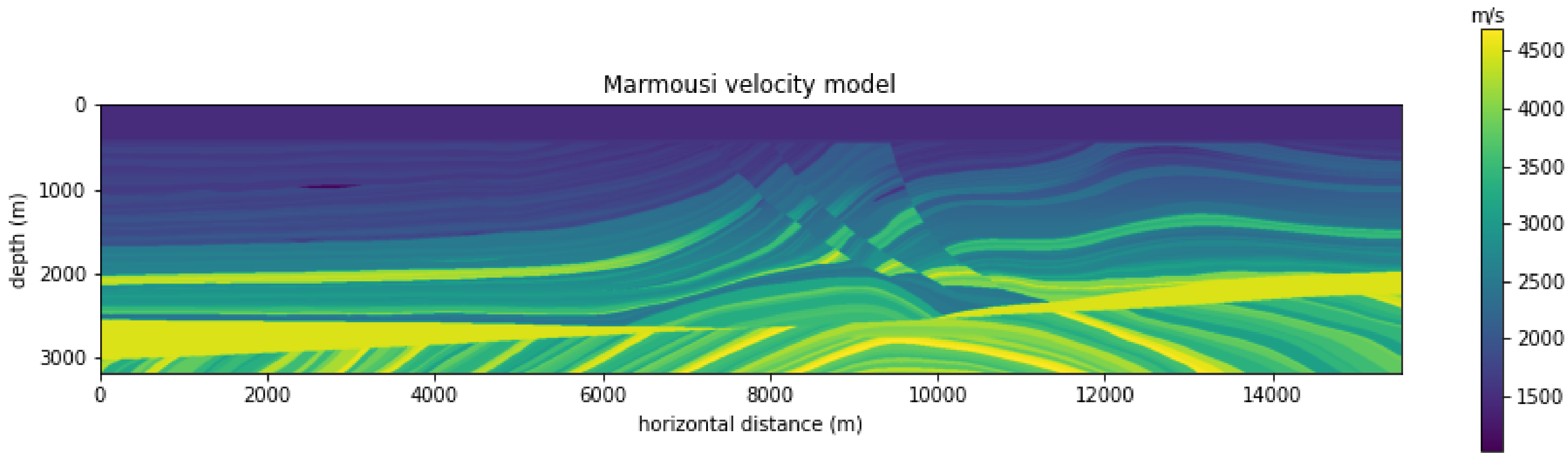

True Label



RTMM-CNN

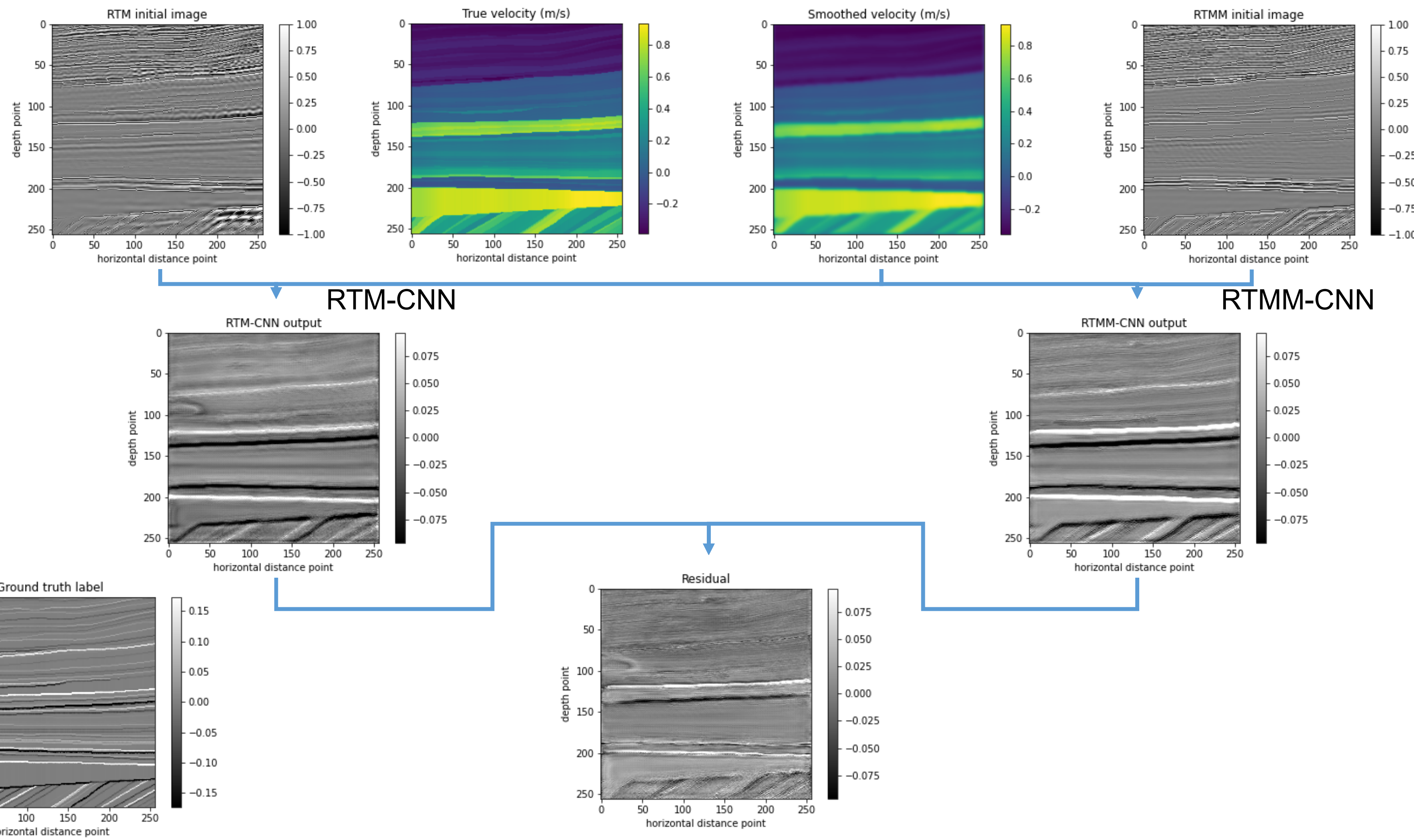


# Numerical Example 2 – Marmousi Model

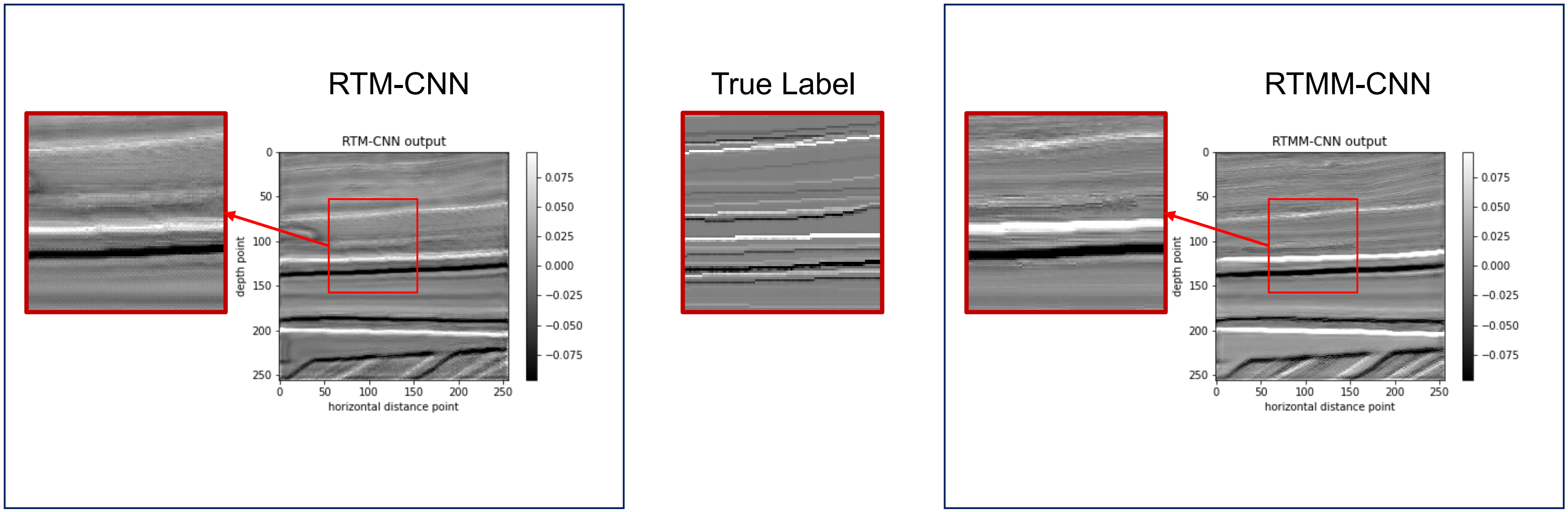



- 1942x400 gridpoints
- dx = dz = 8 meters
- t = 7.2 seconds with dt = 0.8 milliseconds
- ds = 80 meters, dg = 16 meters; ns = 193, ng = 970

# Numerical Example 2 – Marmousi Model

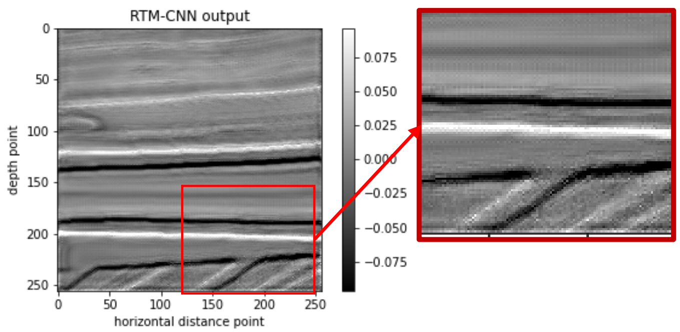


# Numerical Example 2 – Marmousi Model

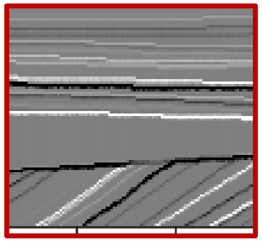


# Numerical Example 2 – Marmousi Model

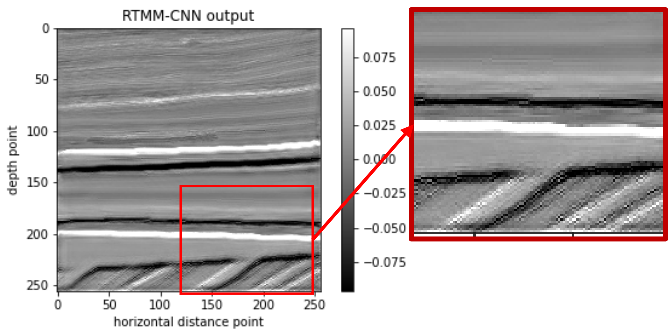
RTM-CNN



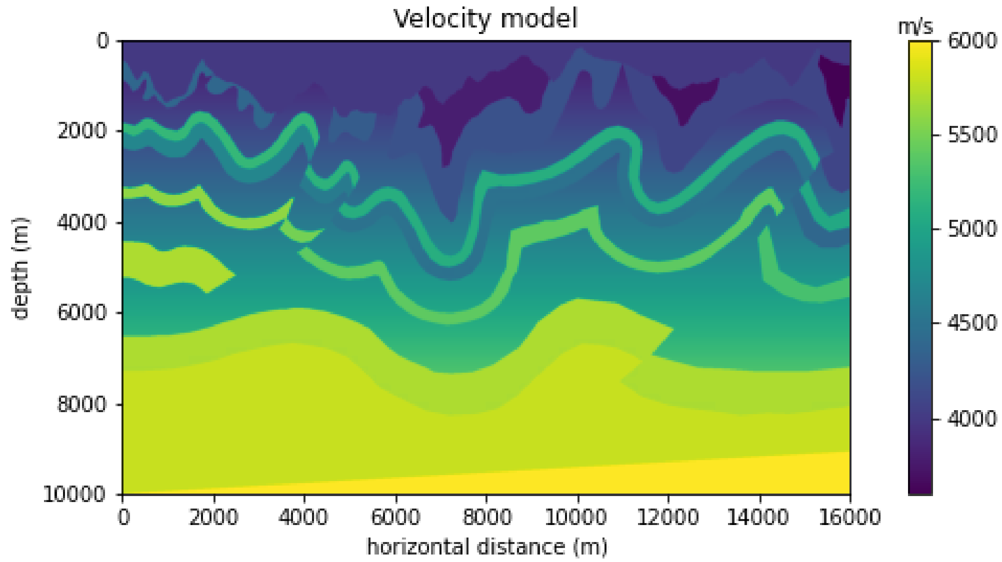

True Label



RTMM-CNN

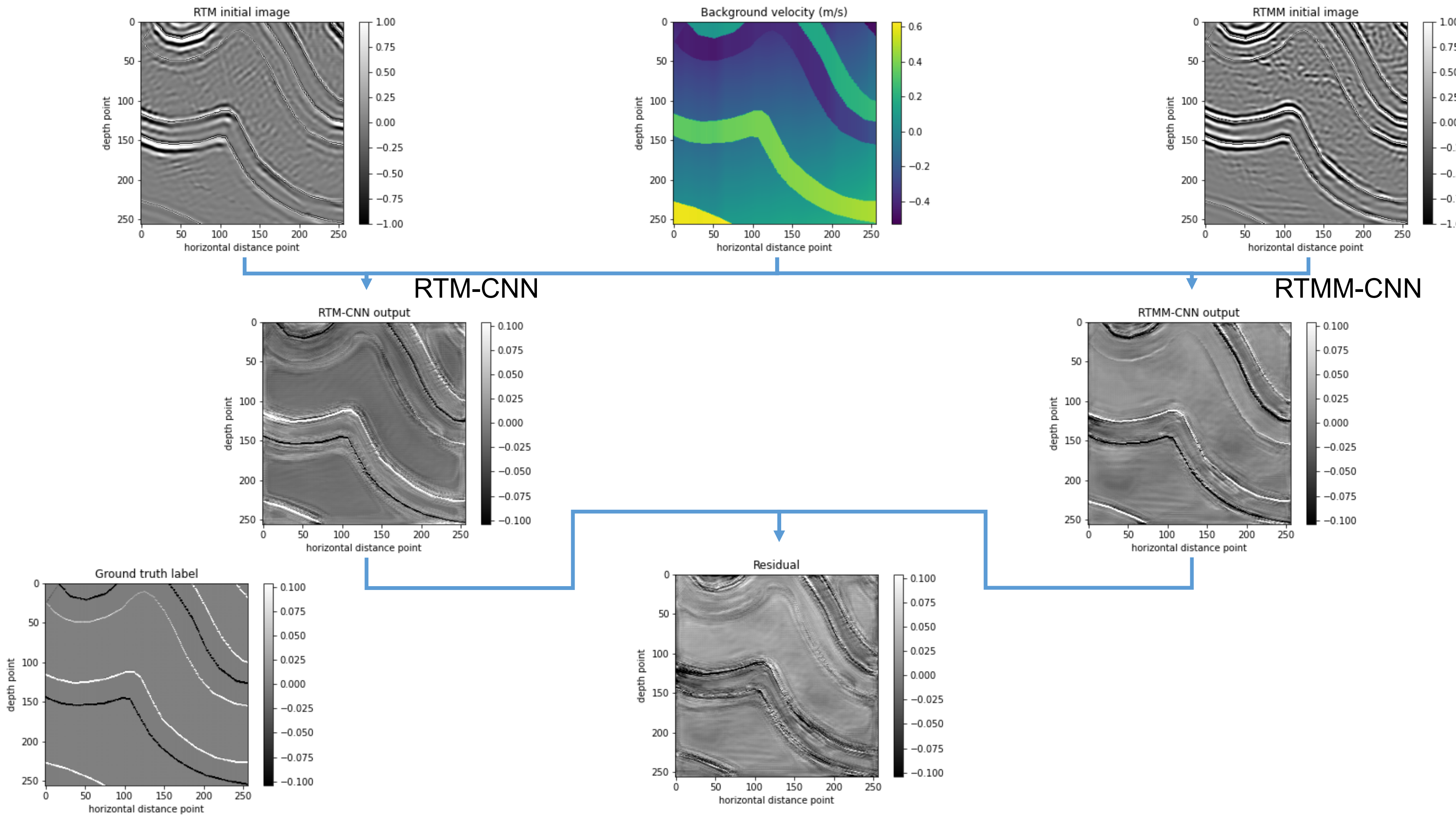


# Numerical Example 3 – Foothill Model



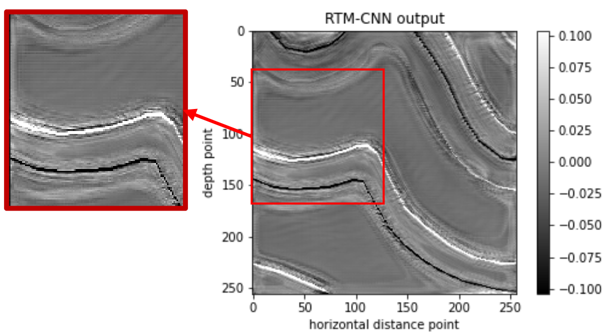

- 1600x1000 gridpoints
- dx = dz = 8 meters
- t = 7.2 seconds with dt = 0.8 milliseconds
- ds = 80 meters, dg = 16 meters; ns = 99, ng = 798

# Numerical Example 3 – Model tested on the Foothill Model with an **accurate velocity input**

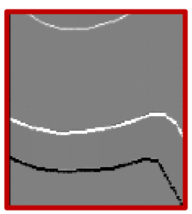


## Numerical Example 3 – Model tested on the Foothill Model with an **accurate velocity input**

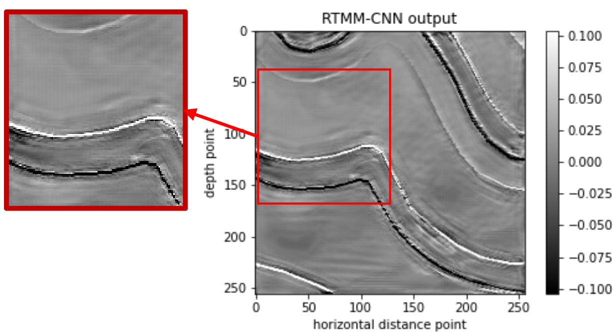
RTM-CNN




True Label

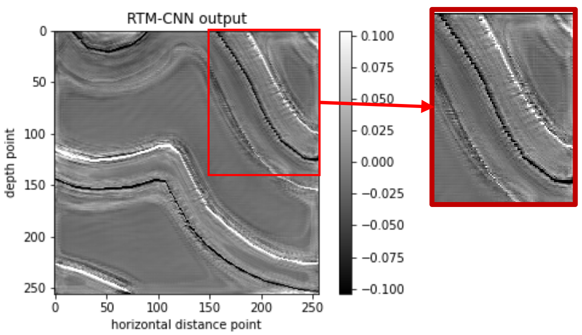


RTMM-CNN

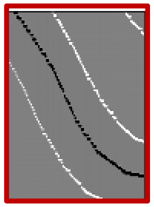


# Numerical Example 3 – Model tested on the Foothill Model with an **accurate velocity input**

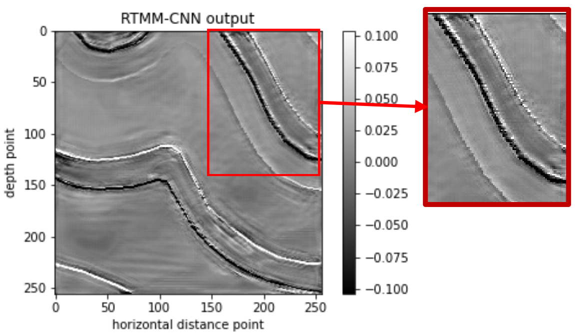
RTM-CNN



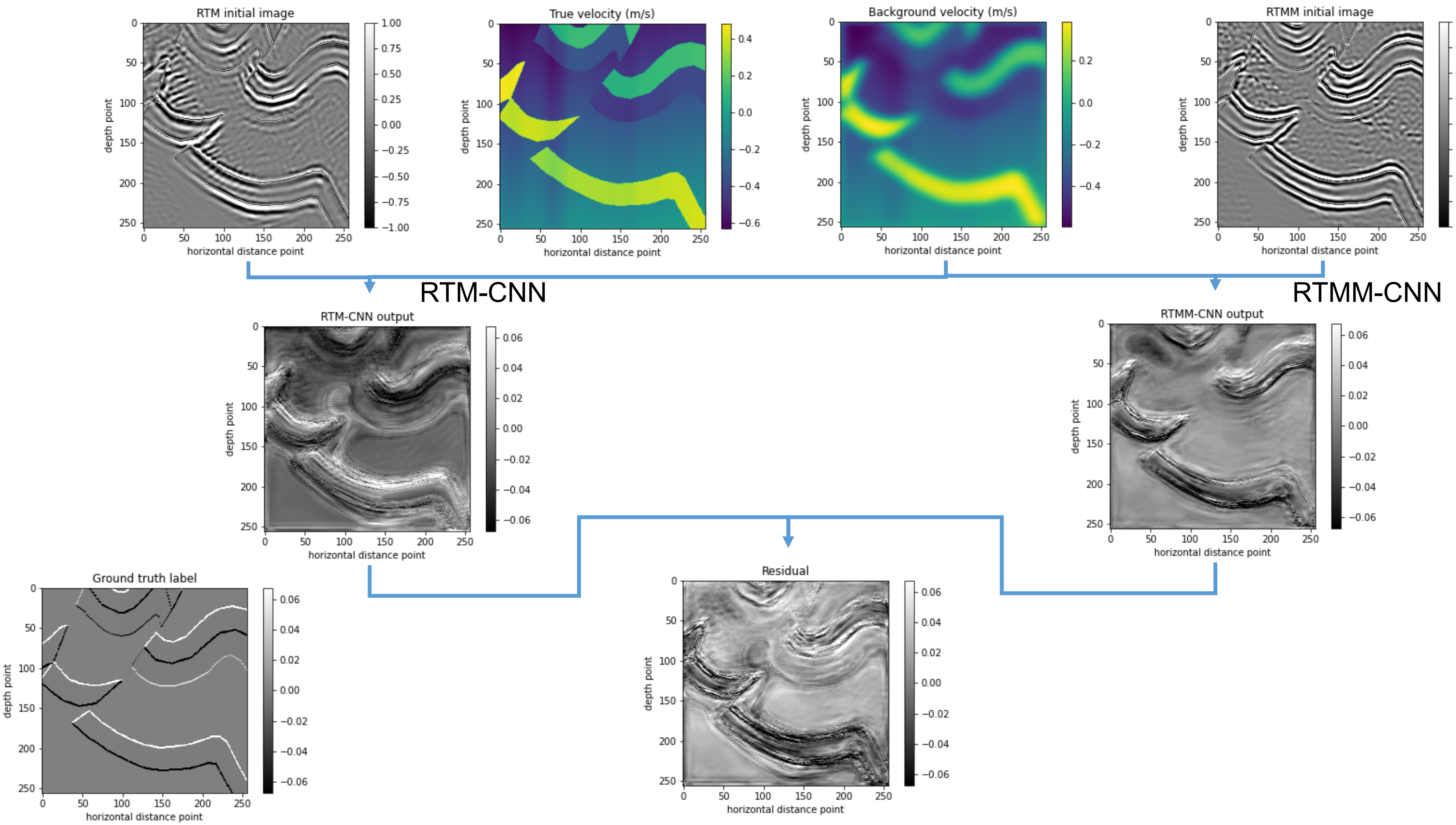

True Label



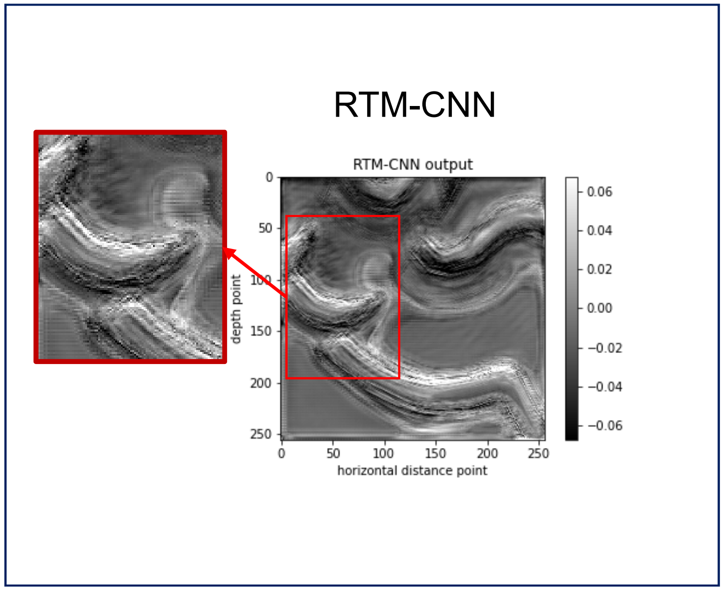
RTMM-CNN



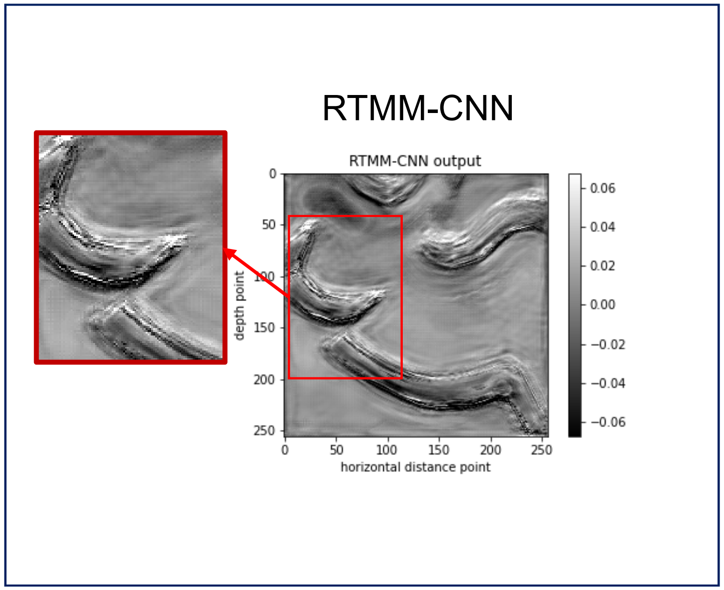
# Numerical Example 4 – Model tested on the Foothill Model with a **smoothed velocity input**



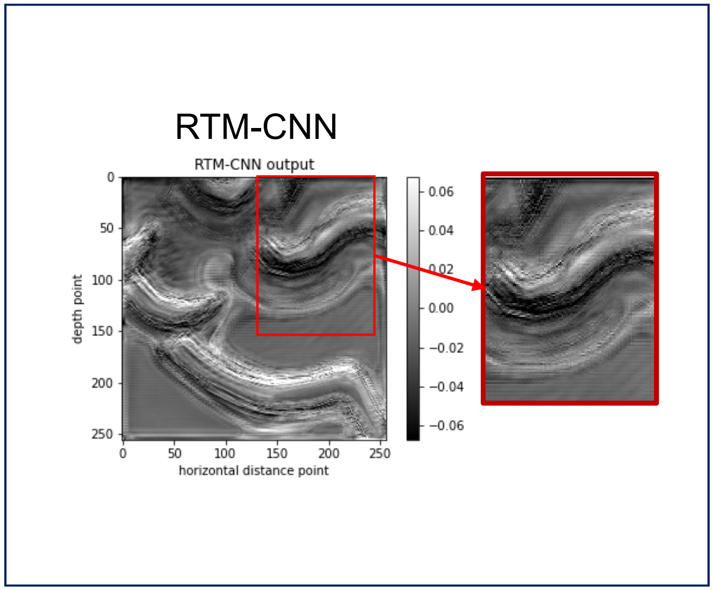
# Numerical Example 4 – Model tested on the Foothill Model with a **smoothed velocity input**

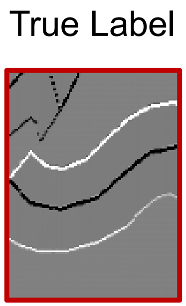


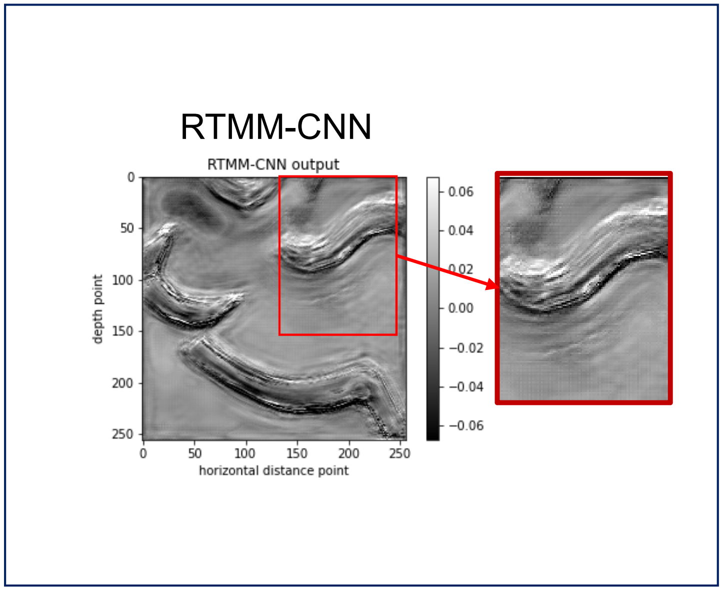




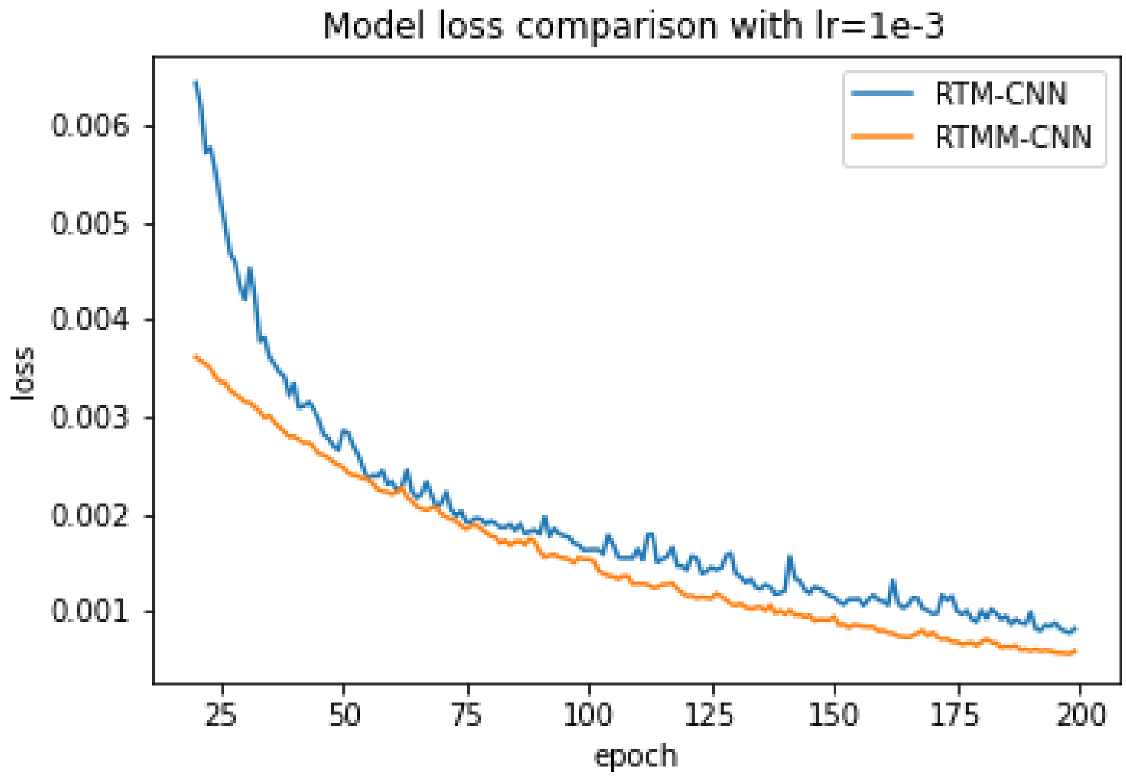
# Numerical Example 4 – Model tested on the Foothill Model with a **smoothed velocity input**



# Model Performance Evaluation



# Consideration – model dependence on the input background velocity model

- To check if this proposed model depends heavily on the input background velocity model:

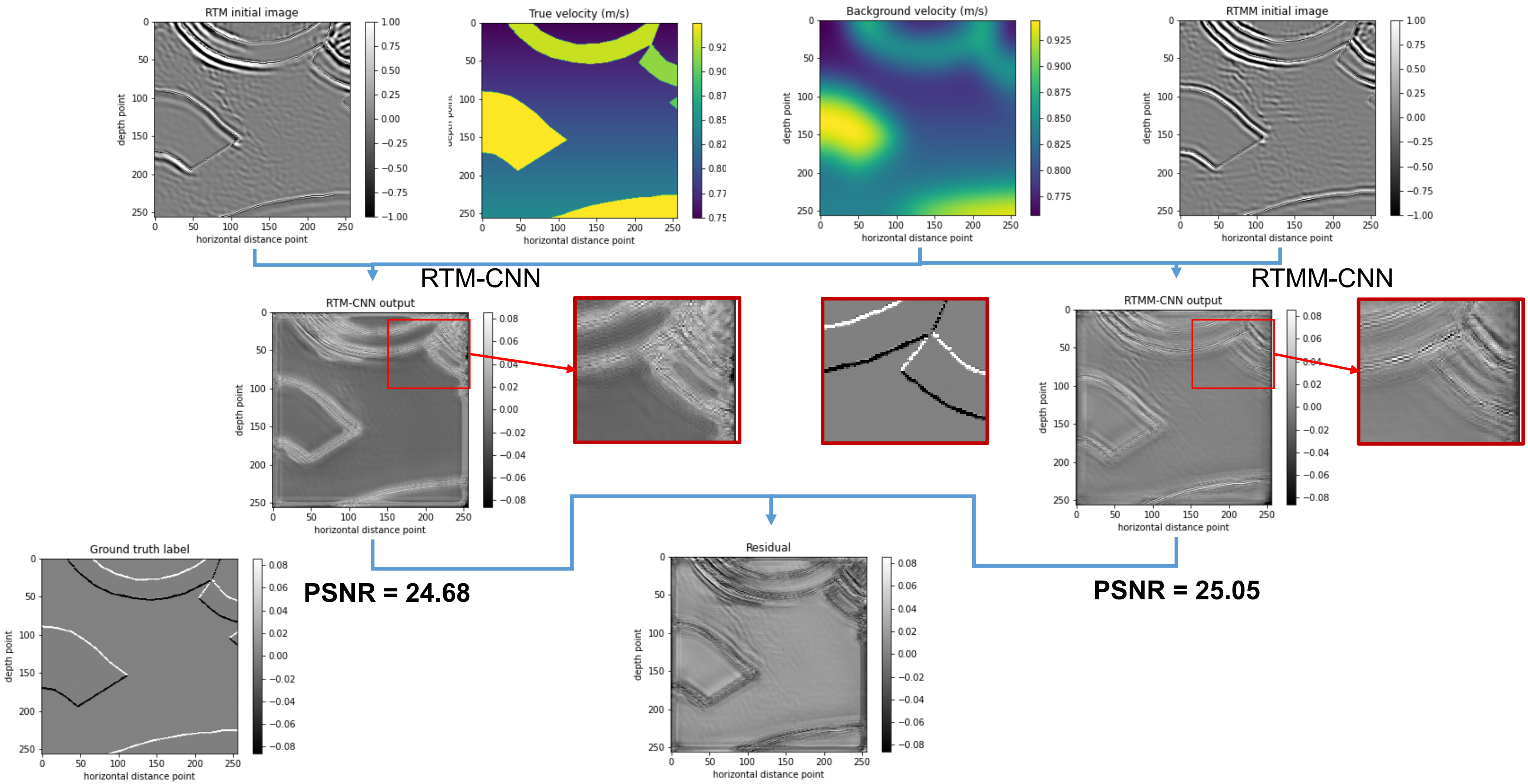
Test 1: apply a larger gaussian smooth filter with $\sigma_x = 10$ and $\sigma_y = 15$

Test 2: remove the background velocity model completely

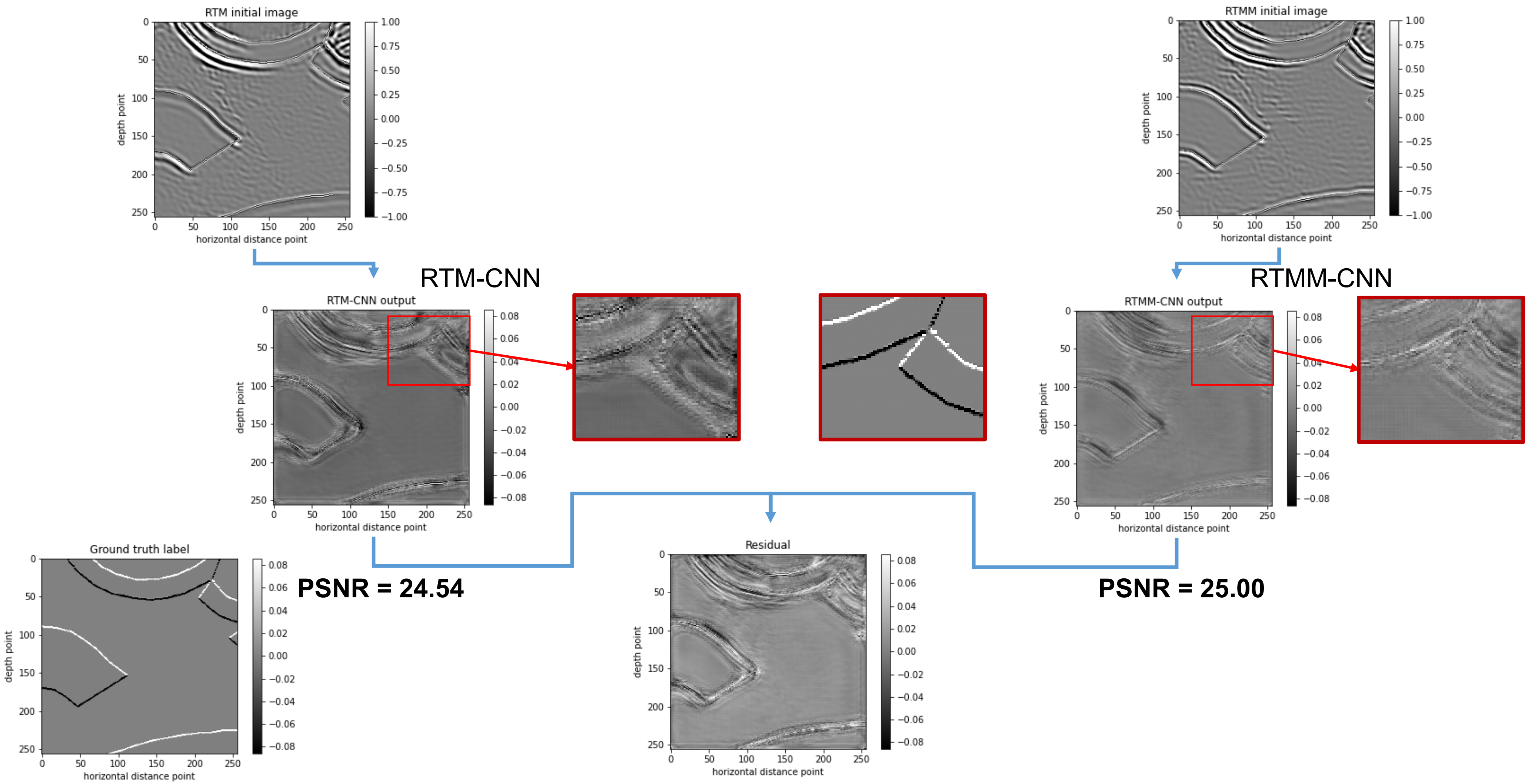
- Peak signal-to-noise ratio (PSNR) is used to evaluate the model performance:

$$\mathrm{PSNR} = 20 * \log_{10}\left(\frac{\mathrm{MAX}_I}{\sqrt{\mathrm{MSE}}}\right) \qquad (9)$$

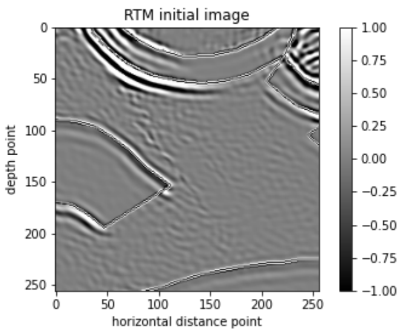
# Test 1: Using a more smoothed background velocity model



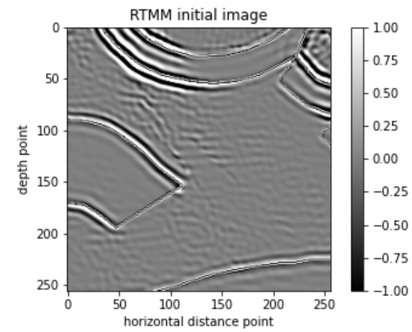
# Test 2: Removing the background velocity input

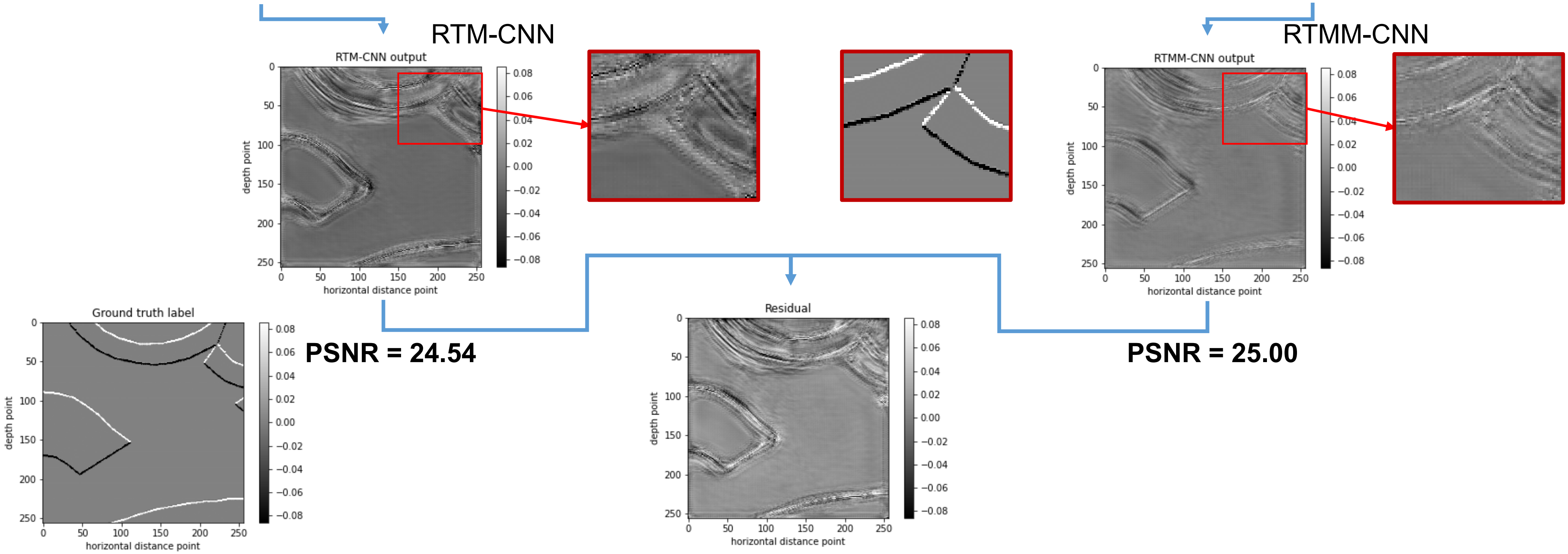


# Test 2: Removing the background velocity input




| Table 1: PSNR comparison in the two tests. | | |
|---|---|---|
| | PSNR (RTM-CNN) | PSNR (RTMM-CNN) |
| Using a smoothed velocity input | 24.68 | 25.05 |
| Removing the velocity input | 24.54 | 25 |



# Conclusion and Future Work

- Both RTM-CNN and RTMM-CNN can have some tolerance on the initial background velocity model.
- RTMM-CNN can recover major structures and thin layers with higher resolution and improved accuracy compared with RTM-CNN.
- The next step is to let the model learn how to predict a steady reflectivity when given a more smoothed input and field data.
- Find a way to improve the model performance on the shadowed zone.

# Acknowledgement


- CREWES industrial sponsors
- CREWES students and staffs
- China Scholarship Council (CSC)
- Natural Science and Engineering Research Council of Canada (NSERC)

# Reference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# Thank you!