ENGINEERING in MEDICINE and BIOLOGY
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# Hybrid Neural Network for Photoacoustic Imaging Reconstruction

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# Outline

1. Background
2. Method
3. Experiments and Results
4. Conclusion and Future works

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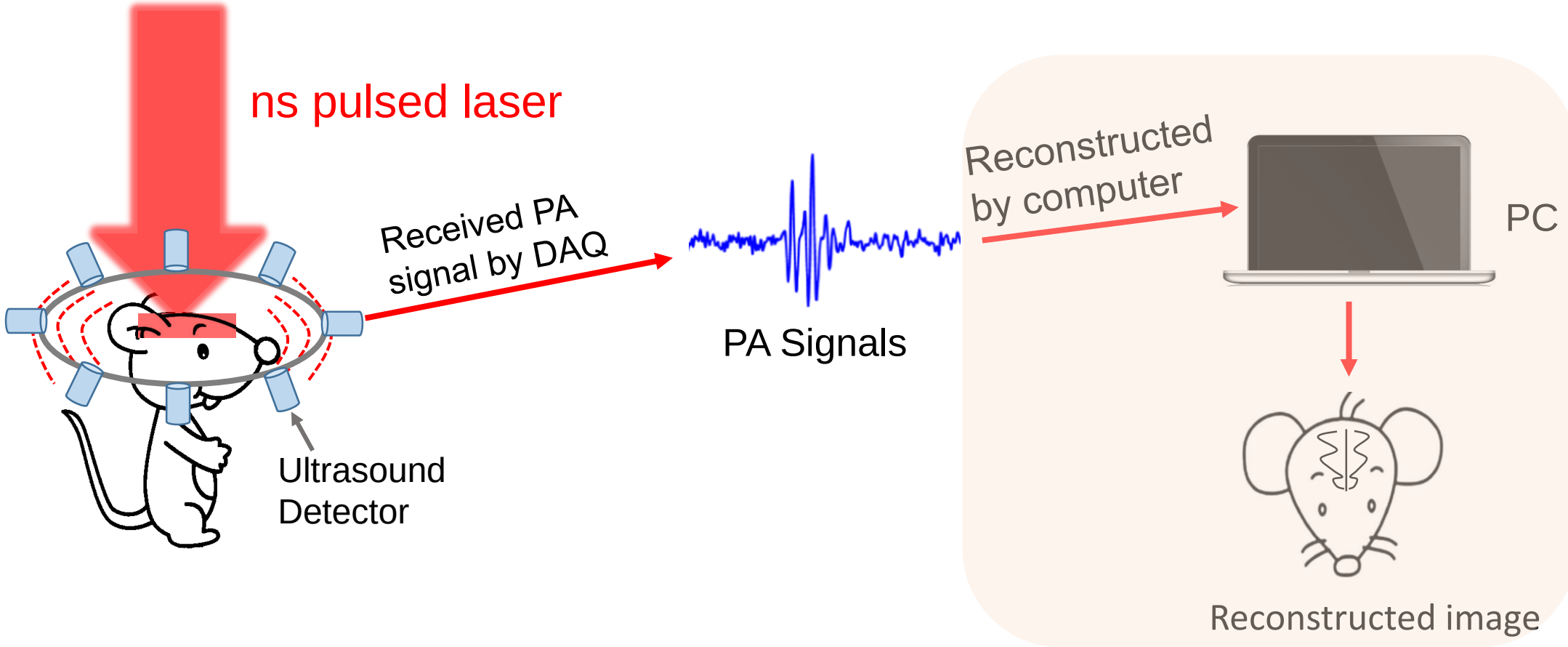
# Background

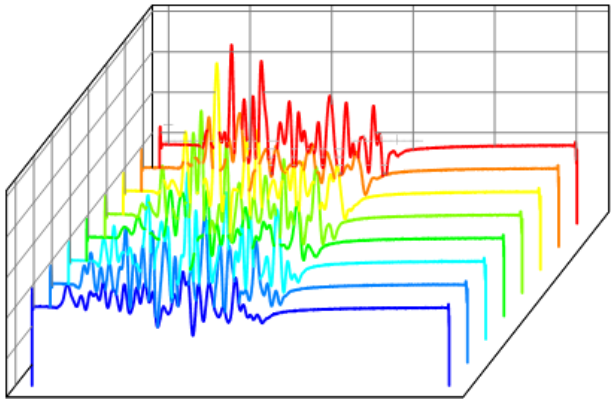
The photoacoustic (PA) effect is the physical basis for PAT

*Light illumination, Light absorption, Temperature rise, Thermoelastic expansion, Ultrasonic emission*



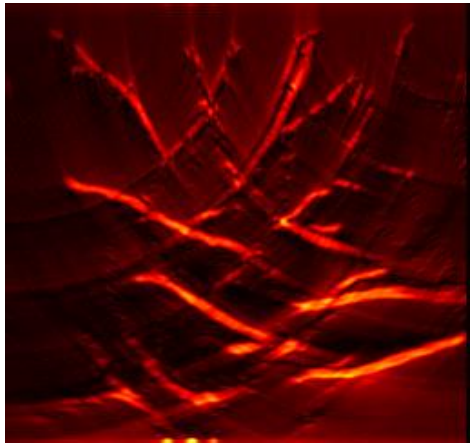
# Background

## Reconstruction



Raw PA signals

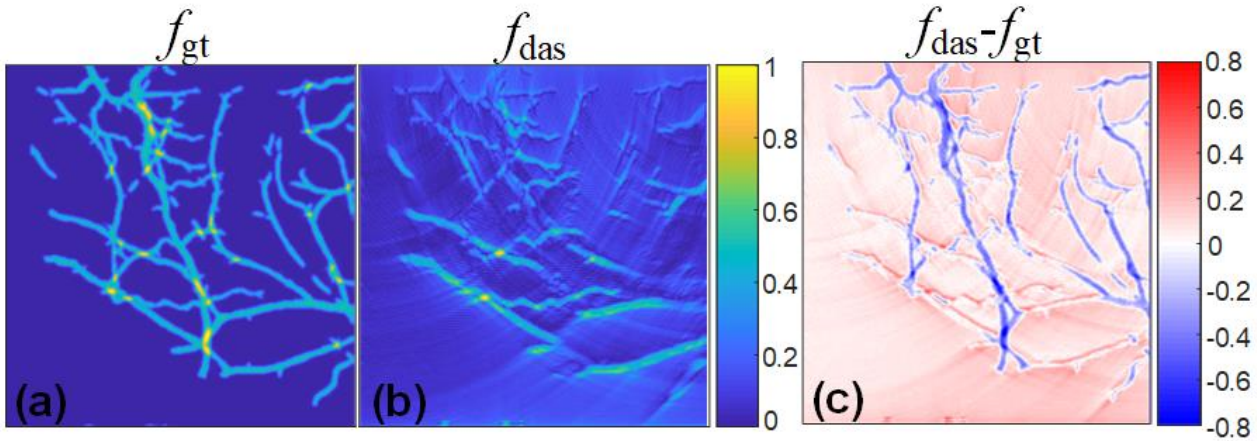
DAS/FBP/TR



Reconstructed PA image

e.g. DAS: delay the time points at different pixel for every channel.

Imperfect reconstruction!



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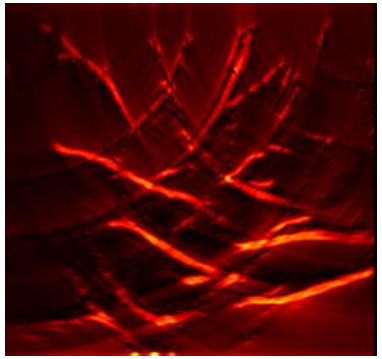
# Method

Rough PA image



Encoder II

Y-Net

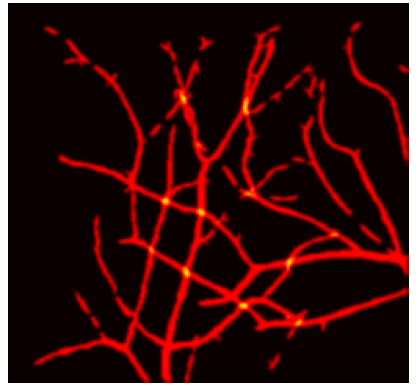
DAS/FBP/TR

Raw PA Signals
2560×128

Encoder I

Decoder

128×128

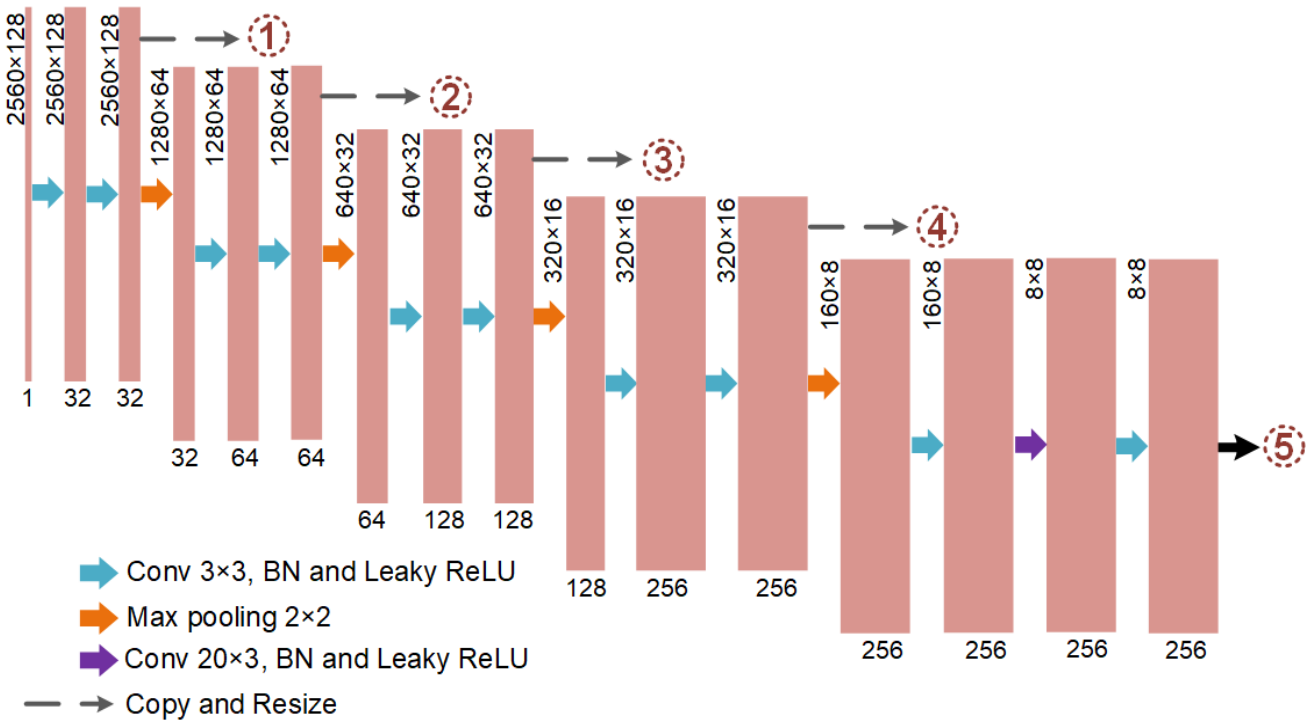


Final PA image

$$\arg\min_{\Theta} \mathbb{E}_{(f^*,b),f} \left\| \mathcal{N}(\Theta, b, f^*) - f \right\|_2^2$$

# Method

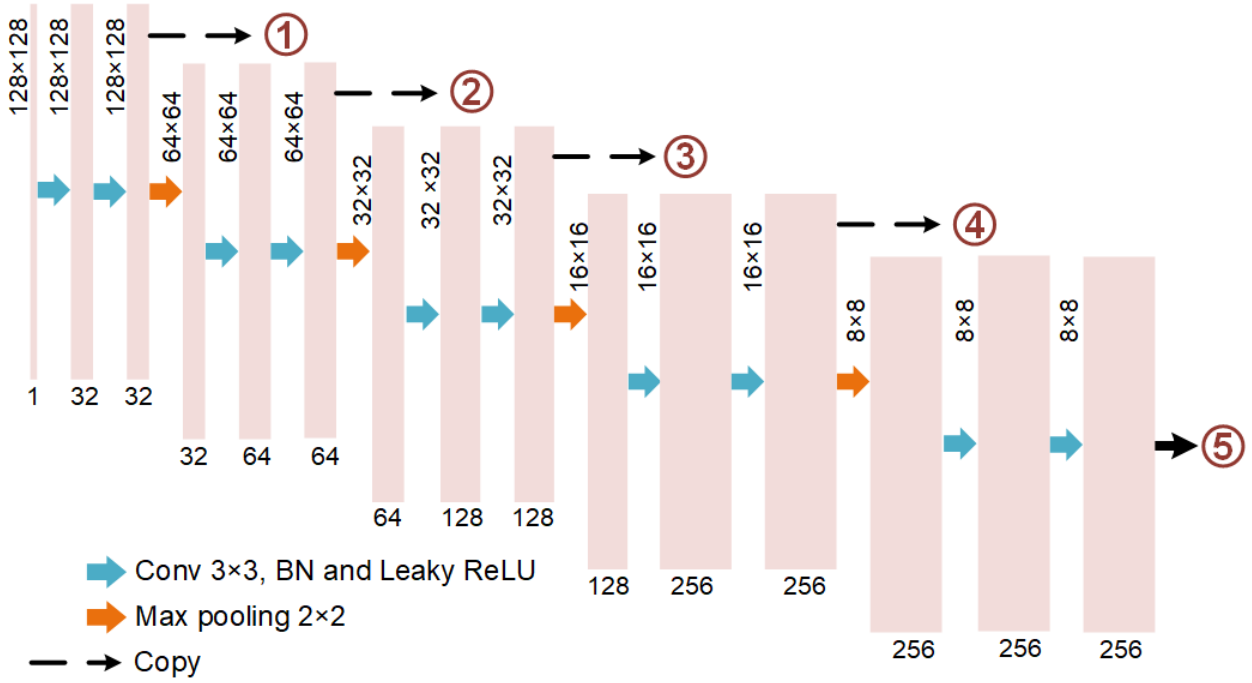
## Encoder I




- Every layer unit is composed of two 3×3 convolution, batch normalization and leaky ReLU;
- An extra 20×3 convolution translates the 160×8 features map to 8×8 in bottom layer;
- A larger receptive field is desirable to focus more information in time dimension;
- Every layer shared their features with the Decoder mirrored layers by resizing and skipping connection

# Method

## Encoder II

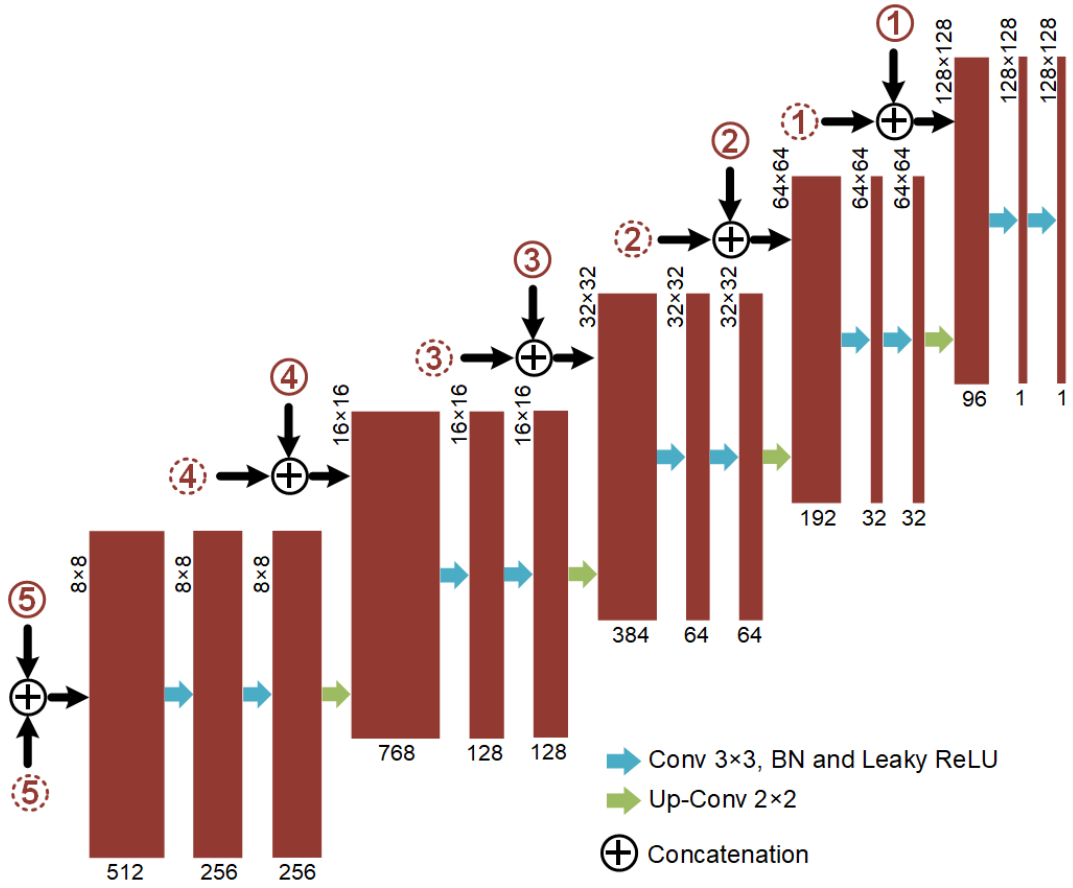



- Every layer unit is also composed of two 3×3 convolution, batch normalization and leaky ReLU;
- Taking the image reconstructed from raw PA data by DAS;
- Skip connections retain many low-level (texture) information.

# Method

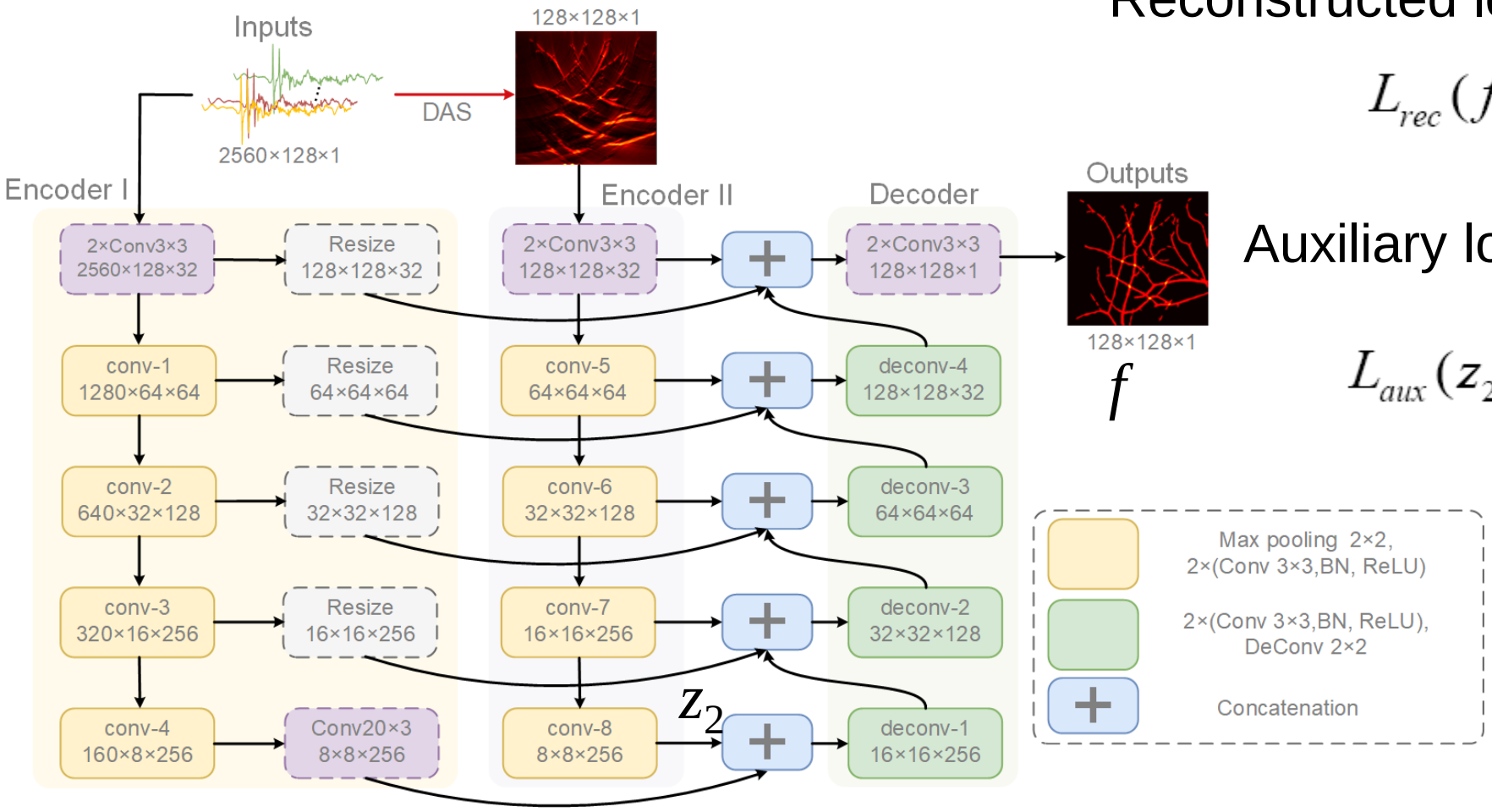
## Decoder

- Reversed layers compared with Encoder II;
- Converging the features from two encoders;
- Decoder is optimized for hybrid reconstruction



# Method

## The Global Architecture




Reconstructed loss:

$$L_{rec}(f) = \frac{1}{2}\left\| f - gt \right\|_F^2 ;$$

Auxiliary loss:

$$L_{aux}(z_2) = \frac{1}{2}\left\| z_2 * \kappa^{\mathrm{T}} - R(gt) \right\|_F^2$$

$$L_{total} = L_{rec} + \lambda L_{aux}$$

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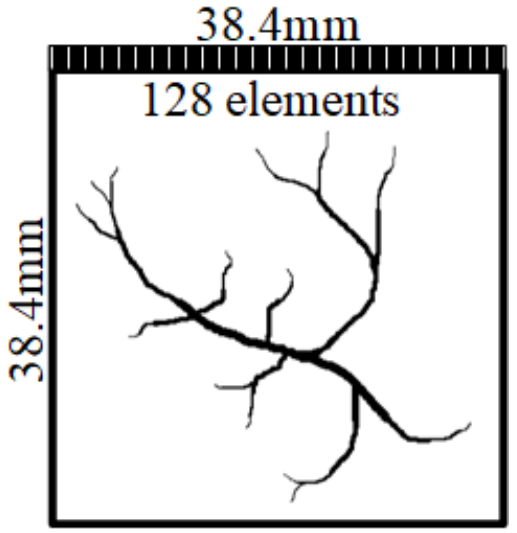
# Experiments

- Deep-learning-based approach is a data-driven method;
- The MATLAB toolbox k-Wave is used to generate the training data;
- The segmented vessel can be deployed with initial pressure distribution.

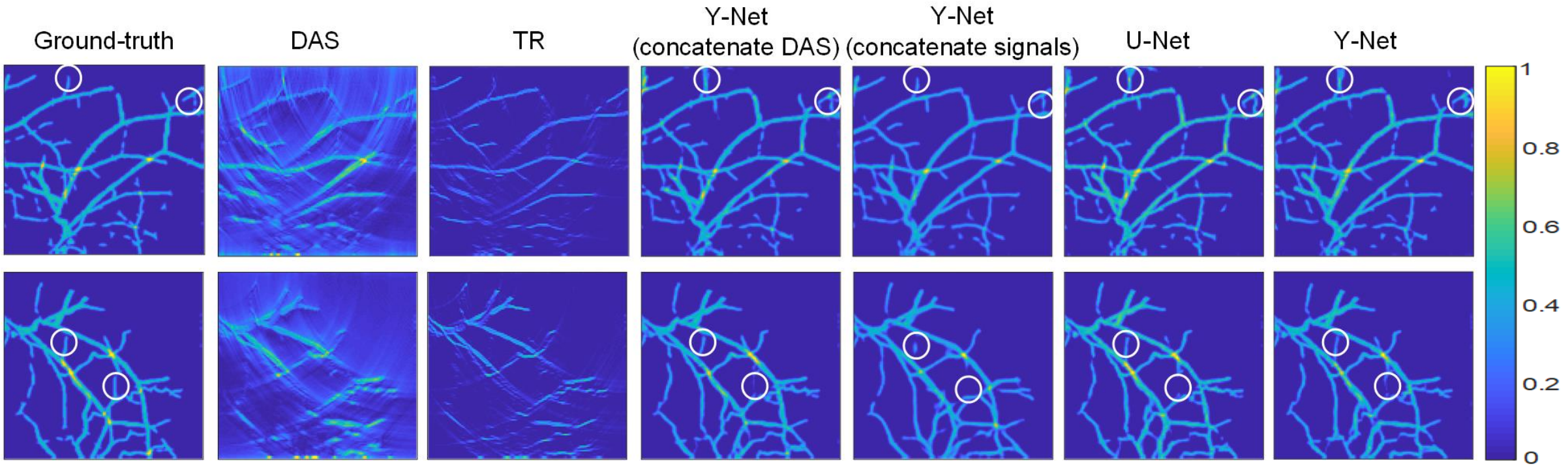
# Experiments

- The sample is placed in the 38.4×38.4 mm region;
- The linear array probe with 128 elements receive 2560×128 PA signal;
- All images have 128×128 pixels;
- Acoustic speed is set as 1500 m/s;
- The center frequency of the transducer is set as 7 MHz with 80% fractional bandwidth;
- The dataset consists of 4700 training sets and 400 test sets.



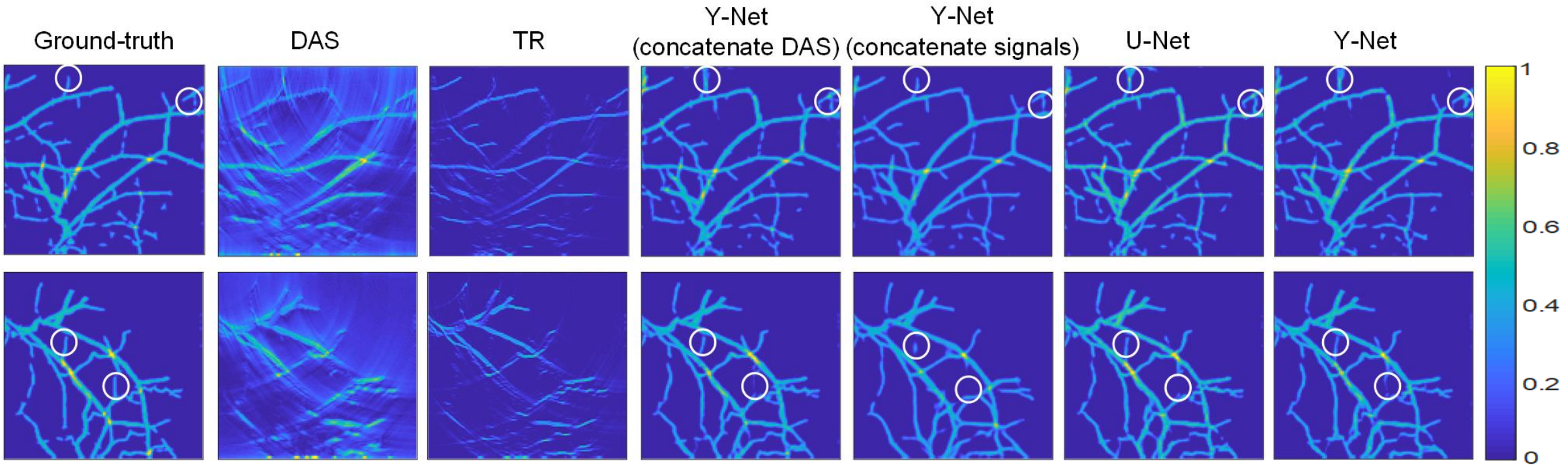

The illustration of the simulation setup

# Results




| | DAS | TR | Y-Net (DAS) | Y-Net (signals) | U-Net | Y-Net |
|---|---|---|---|---|---|---|
| **SSIM** | 0.2032 | 0.5587 | 0.8988 | 0.8622 | 0.9002 | **0.9119** |
| **PSNR** | 17.3626 | 17.8482 | 25.2708 | 23.9152 | 25.0032 | **25.5434** |
| **SNR** | 1.7493 | 2.2350 | 9.6577 | 8.105 | 9.3233 | **9.9291** |

# Results




| | DAS | TR | Y-Net (DAS) | Y-Net (signals) | U-Net | Y-Net |
|---|---|---|---|---|---|---|
| **Time(Second)** | 0.25 | 2 | 0.0309 | 0.0299 | 0.0189 | 0.0326 |

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# Conclusion

- The artifacts are essential to limited-view photoacoustic tomography for conventional algorithms;
- We proposed Y-Net, which consists of two intersecting encoder paths;
- This approach fills the gap between existing direct-processing and post-processing methods;
- A main texture come from Encoder II; The latent features come from Encoder I.

# Future works

- The *in vivo* data need be validated on our method;
- Fill the gap between training data and other data;
- The model-based methods that propose a deep learning network to train the regularization may further help to improve the non-iterative deep-learning-based reconstruction.

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# Thank you!

Q&A

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