



Ki-GAN: Knowledge Infusion Generative Adversarial Network for Photoacoustic Image Reconstruction *in vivo*

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- Photoacoustic imaging (PAI) is a hybrid imaging technique based on the photoacoustic (PA) effect that is excited PA wave by a laser pulse.
- Image reconstruction is an essential topic in photoacoustic imaging, which is unfortunately an ill-posed problem due to the complex and unknown optical/acoustic parameters in tissue.
- The imperfection of conventional algorithms is the existence of artifacts, which results in distorted images, especially in sparse view configuration.
- ◆ In this work, we propose Knowledge Infusion Generative Adversarial Network (Ki-GAN) to boost reconstruction performance.
- ◆ The knowledge comes from two sources: 1) Traditional signal processing inspiration (e.g. raw PA signals); 2) Traditional certified reconstruction algorithm (e.g. PA images reconstructed from back-projection).
- ◆ Our primary contribution is to suggest a novel framework to infuse the raw PA signals and conventional reconstruction image, and achieve better results compared with prior work.

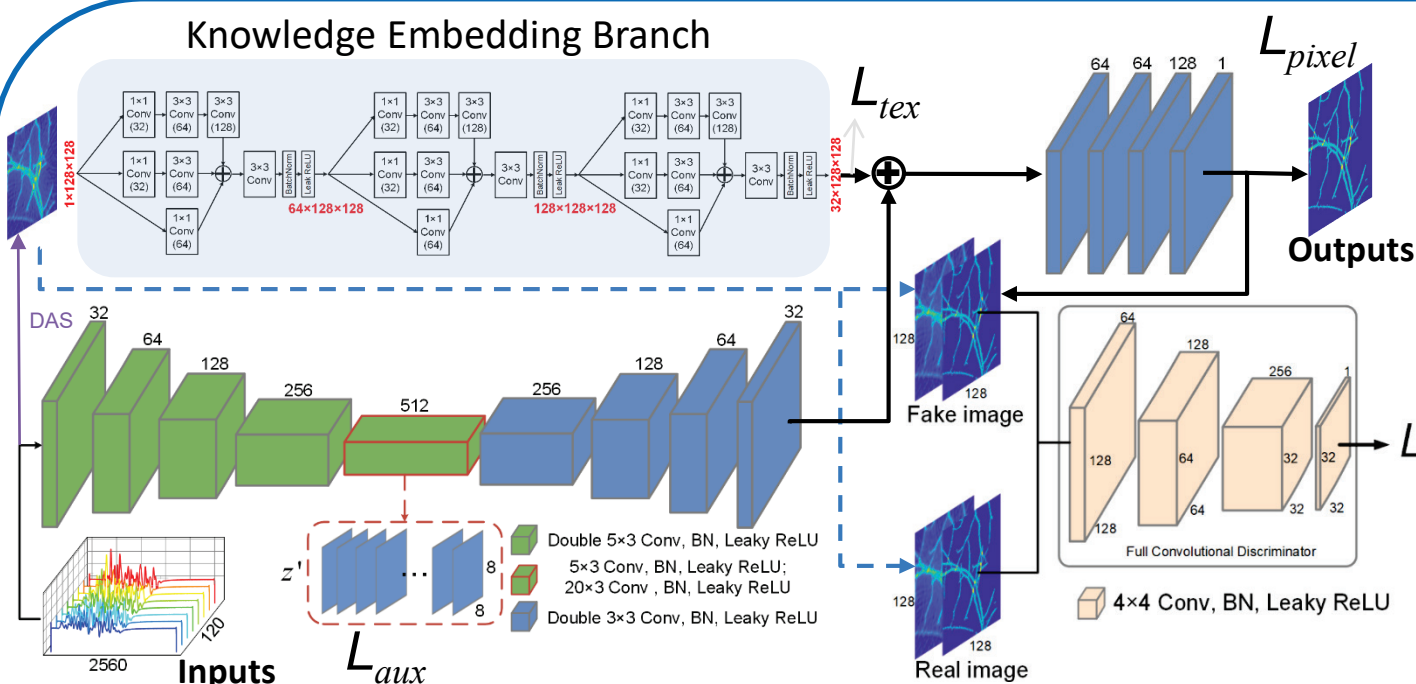


Figure 1 The architecture of Ki-GAN. DAS: delay-and-sum, which is a conventional reconstruction algorithm; KEB: knowledge embedding branch. Dotted area z' is taken to a convolutional layer and obtain the latent feature (penalize the encoder by L_{aux}). Note that we use convolutional kernel with 4×4 size for Discriminator, the receptive fields of output can still cover the entire input image.

$$L_{total} = \lambda_{adv} L_{advG} + \lambda_{pix} L_{pixel} + \lambda_{aux} L_{aux} + \lambda_{tex} L_{tex} \quad \text{where } \lambda_{adv}, \lambda_{pix}, \lambda_{aux}, \lambda_{tex} \text{ are hyper-parameters.}$$

- The data set are generated by MATLAB toolbox k-Wave from public database.
- To expand the data volume, firstly, the complete blood vessel is segmented into four equal parts; and then randomly transform (e.g. rotations and transpositions) and merge two segmented blood vessels.
- We design a new Auto-Encoder (AE) with signal processing knowledge using a large kernel size and supervise the image feature by L_{aux} .
- We also embed a certified algorithm (DAS) into image feature by the Knowledge Embedding Branch.
- PatchGAN is used to discriminate the outputs of Generator.

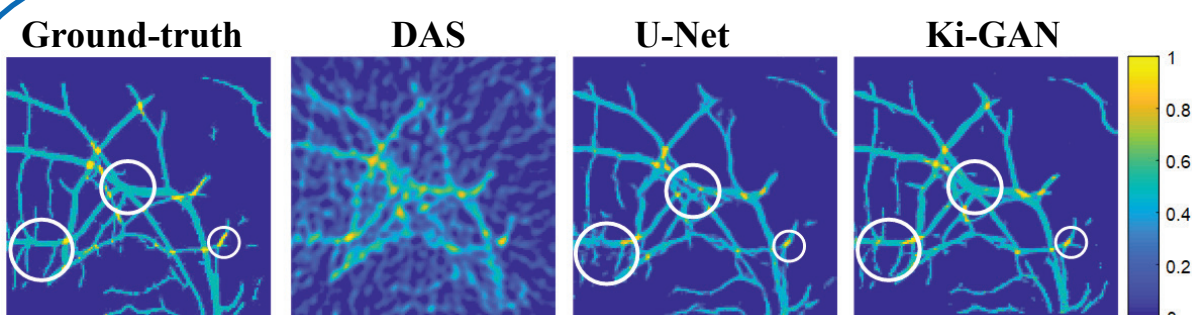


Figure 2 Example of quantitative comparison using sparse-sampled (40 channels) data. From left to right: ground-truth, delay-and-sum, U-Net and Ki-GAN. The white circles indicate the local details.

Table 1 Evaluation results of different models for sparse-sampled (40 channels) data.

| Algorithms | SSIM | PSNR | SNR |
|------------|---------------|----------------|---------------|
| DAS | 0.1842 | 15.5123 | 1.5333 |
| U-Net | 0.8174 | 21.348 | 7.4689 |
| Ki-GAN | 0.8617 | 22.7398 | 8.7607 |

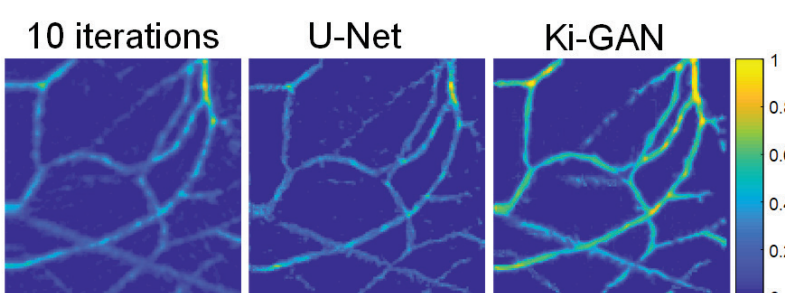


Figure 3 The vessel imaging of rat thigh (full-sampled). From left to right: iterative algorithm with 10 iterations, U-Net and Ki-GAN.

- Conventional algorithms (DAS) cannot avoid the artifacts and difficult to distinguish vessels in sparse view.
- The white circles marked three details in Figure 2, showing that the result of Ki-GAN identifies with ground-truth image more closely compared with U-Net.
- Ki-GAN possesses a stronger contrast and fewer artifacts compared with other two methods in Figure 3.
- The time consumption of the iterative reconstruction algorithm with 10 iterations, U-Net and Ki-GAN are 331.51s, 0.01s and 0.025s in Figure 3.

Ablation studies and comparative experiments show that the proposed model can perform very well in full-sampled data, sparse-sampled data, and *in vivo* experimental data.