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**Rising role of artificial intelligence in image reconstruction for biomedical imaging**

Chen XL *et al.* AI in biomedical image reconstruction

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**Abstract**

In this editorial, we review recent progress on the applications of artificial intelligence (AI) in image reconstruction for biomedical imaging. Because it abandons prior information of traditional artificial design and adopts a completely data-driven mode to obtain deeper prior information *via* learning, AI technology plays an increasingly important role in biomedical image reconstruction. The combination of AI technology and the biomedical image reconstruction method has become a hotspot in the field. Favoring AI, the performance of biomedical image reconstruction has been improved in terms of accuracy, resolution, imaging speed, *etc*. We specifically focus on how to use AI technology to improve the performance of biomedical image reconstruction, and propose possible future directions in this field.

**Key words:** Biomedical imaging; Image reconstruction; Artificial intelligence; Machine learning; Deep learning; Tomography

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**Core tip:** Three-dimensional biomedical imaging plays an important role in biology and medicine. We review recent progress on the applications of artificial intelligence (AI) in image reconstruction for biomedical imaging. We specifically focus on how to use AI technology to improve the performance of biomedical image reconstruction and propose possible future directions in this field. We believe that, with further development, AI technology will play an increasingly important role in biomedical image reconstruction.

**BACKGROUND**

Biomedical imaging plays an important role in biology and medicine. In particular, three-dimensional (3D) imaging mode based on an image reconstruction technique, such as computed tomography (CT), magnetic resonance imaging (MRI), positron emission tomography (PET), photoacoustic tomography (PAT), and 3D optical imaging, allow biologists and physicians to visualize the structural, cellular, and functional information stereoscopically. Image reconstruction in 3D biomedical imaging is a type of inverse problem, which is used to reconstruct the distribution of this information in the living body by using the physical signals acquired from outside of the body. Research on the image reconstruction algorithm has always been an important issue to promote the development and innovation of biomedical imaging equipment. However, due to several reasons, such as the limitation of imaging time and dose (contrast medium or radiation dose), insufficiency of the measurements, inherent noise and other interference doping in the original signals, the traditional image reconstruction techniques cannot achieve good performance. For example, there are trade-offs in optimal imaging accuracy, spatial resolution and imaging speed, which have been challenges in the field of biomedical image reconstruction. The rapid development of artificial intelligence (AI) technology brings new opportunities for biomedical image reconstruction. AI abandons prior information of traditional artificial design, and adopts a completely data-driven mode to obtain deeper prior information *via* learning. Currently, the combination of AI and the biomedical image reconstruction method has become a hotspot in the field.

**ADVANCES**

Recently, AI plays an increasingly important role in image reconstruction of 3D biomedical imaging, including both clinical and preclinical biomedical imaging technologies such as CT, MRI, PET, PAT, and 3D optical imaging. In CT reconstruction, AI technology mainly focuses on solving two problems: CT reconstruction with low radiation dose and CT reconstruction with a small amount of view measurements[1-6].For example, Chen *et al*[1] integrated the autoencoder, deconvolution network, and shortcut connections into the residual encoder-decoder convolutional natural network for low-dose CT imaging, which demonstrated great potential for high-speed imaging with good noise reduction, structural preservation, and lesion detection. For CT reconstruction with a small amount of view measurements, it mainly involves a small amount of view reconstruction based on limited angles[2-4] and sparse view reconstruction based on full angles[5-7]. With the help of the deep learning framework, researchers can obtain a much clearer edge and fine structural information through a small amount of measured data, to achieve the best imaging quality with faster imaging speed[5-7]. The use of AI technology in MRI image reconstruction has attracted an increasing amount of attention, and much progress has been made in recent years. In these works, by means of machine learning or deep learning framework, MRI image reconstruction can be much improved by reducing noise or artifacts[8], enhancing spatial resolution or details[9-12], accelerating imaging speed[13-16],and improving image accuracy and quality[17-21].AI-based image reconstruction techniques have also been applied to clinical studies, for example the TrueFidelity[22], a deep learning-based image processing platform developed by General Electric Healthcare and the Advanced intelligent clear-IQ Engine[23], developed by Canon Medical Systems Corporation.

In functional or molecular imaging, AI technology is mainly used to improve the quality of reconstructed images[24-38].For example, by using AI technology, high-quality PET images can be reconstructed from low-dose and ultra-low-dose radionuclides[24,25].The whole neural network can solve the storage space challenge in PET and realize the direct reconstruction of large-scale data[28]. With the help of machine learning and deep learning frameworks, the problems existing in PAT image reconstruction caused by limited views or sparse view measurements, including resolution and image quality degradation, can be solved[29-33]. In diffuse light-based 3D optical imaging, it is necessary to establish a mathematical model to describe diffused light propagation in the living body, and then to calculate the target distribution by solving the model in reverse[39,40].However, this mathematical model is usually a simplified linear model that has serious ill-posedness, which results in poor quality of reconstructed images. With the help of the deep learning framework by directly learning the complicated relationship between surface measurements and target distribution inside the body, the quality of the reconstructed image can be greatly improved and the reconstruction time can be reduced[34-38].

**OUTLOOK**

We present recent progresses on AI-based image reconstruction for 3D biomedical imaging. The rising role of AI in image reconstruction includes improving the quality, accuracy, and resolution of the reconstructed image as well as the imaging speed. Furthermore, with the rapid development of AI technology, such a rising role will become increasingly significant. However, there remain several central challenges facing the field. The first one is the generality of machine learning or the deep learning framework. In existing studies, the frameworks are all aimed at specific problems, such as image objects with specific features. Thus, generalization performance and the migration ability of the framework are poor. If a network framework can be developed, which can provide good image reconstruction performance for the imaging objects with various structures and properties, even for all of the biomedical imaging technologies, it will be great progress on AI-based image reconstruction for biomedical imaging. Second, current research needs to use AI technology to reconstruct the measured data into images, and then analyze these images to obtain relevant physiological or pathological information. With the help of AI, it will be significant to obtain physiological and pathological information directly from the measured data, which is also the future direction of the application of AI technology in the field of biomedical imaging. Lastly, the development of machine learning or the deep learning algorithm itself is also an important direction in the field. These efforts are expected to promote the wide applications of AI-based biomedical imaging in biology and medicine.

**REFERENCES**

1 **Chen H**, Zhang Y, Kalra MK, Lin F, Chen Y, Liao P, Zhou J, Wang G. Low-Dose CT With a Residual Encoder-Decoder Convolutional Neural Network. *IEEE Trans Med Imaging* 2017; **36**: 2524-2535 [PMID: 28622671 DOI: 10.1109/TMI.2017.2715284]

2 **Jiang Z**, Chen Y, Zhang Y, Ge Y, Yin FF, Ren L. Augmentation of CBCT Reconstructed From Under-Sampled Projections Using Deep Learning. *IEEE Trans Med Imaging* 2019; **38**: 2705-2715 [PMID: 31021791 DOI: 10.1109/TMI.2019.2912791]

3 **Bubba TA,** Kutyniok G, Lasses M, Marz M, Samek W, Siltanen S, Srinivasan V. Learning the invisible: a hybrid deep learning-shearlet framework for limited angle computed tomography. *Inverse Probl* 2019; **35**: 064002 [DOI: 10.1088/1361-6420/ab10ca]

4 **Fu J**, Dong J, Zhao F. A Deep Learning Reconstruction Framework for Differential Phase-Contrast Computed Tomography With Incomplete Data. *IEEE Trans Image Process* 2020; **29**: 2190-2202 [PMID: 31647435 DOI: 10.1109/TIP.2019.2947790]

5 **Kyong Hwan Jin**, McCann MT, Froustey E, Unser M. Deep Convolutional Neural Network for Inverse Problems in Imaging. *IEEE Trans Image Process* 2017; **26**: 4509-4522 [PMID: 28641250 DOI: 10.1109/TIP.2017.2713099]

6 **Han Y**, Ye JC. Framing U-Net via Deep Convolutional Framelets: Application to Sparse-View CT. *IEEE Trans Med Imaging* 2018; **37**: 1418-1429 [PMID: 29870370 DOI: 10.1109/TMI.2018.2823768]

7 **Nakai H**, Nishio M, Yamashita R, Ono A, Nakao KK, Fujimoto K, Togashi K. Quantitative and Qualitative Evaluation of Convolutional Neural Networks with a Deeper U-Net for Sparse-View Computed Tomography Reconstruction. *Acad Radiol* 2020; **27**: 563-574 [PMID: 31281082 DOI: 10.1016/j.acra.2019.05.016]

8 **Zhu B**, Liu JZ, Cauley SF, Rosen BR, Rosen MS. Image reconstruction by domain-transform manifold learning. *Nature* 2018; **555**: 487-492 [PMID: 29565357 DOI: 10.1038/nature25988]

9 **Chaudhari AS**, Fang Z, Kogan F, Wood J, Stevens KJ, Gibbons EK, Lee JH, Gold GE, Hargreaves BA. Super-resolution musculoskeletal MRI using deep learning. *Magn Reson Med* 2018; **80**: 2139-2154 [PMID: 29582464 DOI: 10.1002/mrm.27178]

10 **Sun L**, Fan Z, Fu X, Huang Y, Ding X, Paisley J. A Deep Information Sharing Network for Multi-Contrast Compressed Sensing MRI Reconstruction. *IEEE Trans Image Process* 2019; **28**: 6141-6153 [PMID: 31295112 DOI: 10.1109/TIP.2019.2925288]

11 **Shi J**, Li Z, Ying S, Wang C, Liu Q, Zhang Q, Yan P. MR Image Super-Resolution via Wide Residual Networks With Fixed Skip Connection. *IEEE J Biomed Health Inform* 2019; **23**: 1129-1140 [PMID: 29993565 DOI: 10.1109/JBHI.2018.2843819]

12 **Zhang J,** Gu Y, Tang H, Wang X, Kong Y, Chen Y, Shu H, Coatrieux J. Compressed sensing MR image reconstruction via a deep frequency-division network. *Neurocomputing* 2020; **384**: 346-355 [DOI: 10.1016/j.neucom.2019.12.011]

13 **Yang G**, Yu S, Dong H, Slabaugh G, Dragotti PL, Ye X, Liu F, Arridge S, Keegan J, Guo Y, Firmin D, Keegan J, Slabaugh G, Arridge S, Ye X, Guo Y, Yu S, Liu F, Firmin D, Dragotti PL, Yang G, Dong H. DAGAN: Deep De-Aliasing Generative Adversarial Networks for Fast Compressed Sensing MRI Reconstruction. *IEEE Trans Med Imaging* 2018; **37**: 1310-1321 [PMID: 29870361 DOI: 10.1109/TMI.2017.2785879]

14 **Lee D**, Yoo J, Tak S, Ye JC. Deep Residual Learning for Accelerated MRI Using Magnitude and Phase Networks. *IEEE Trans Biomed Eng* 2018; **65**: 1985-1995 [PMID: 29993390 DOI: 10.1109/TBME.2018.2821699]

15 **Xiang L**, Chen Y, Chang W, Zhan Y, Lin W, Wang Q, Shen D. Deep Leaning Based Multi-Modal Fusion for Fast MR Reconstruction. *IEEE Trans Biomed Eng* 2019; **66**: 2105-2114 [PMID: 30507491 DOI: 10.1109/TBME.2018.2883958]

16 **Zhang J**, Wu J, Chen S, Zhang Z, Cai S, Cai C, Chen Z. Robust Single-Shot T2 Mapping via Multiple Overlapping-Echo Acquisition and Deep Neural Network. *IEEE Trans Med Imaging* 2019; **38**: 1801-1811 [PMID: 30714913 DOI: 10.1109/TMI.2019.2896085]

17 **Schlemper J**, Caballero J, Hajnal JV, Price AN, Rueckert D. A Deep Cascade of Convolutional Neural Networks for Dynamic MR Image Reconstruction. *IEEE Trans Med Imaging* 2018; **37**: 491-503 [PMID: 29035212 DOI: 10.1109/TMI.2017.2760978]

18 **Quan TM**, Nguyen-Duc T, Jeong WK. Compressed Sensing MRI Reconstruction Using a Generative Adversarial Network With a Cyclic Loss. *IEEE Trans Med Imaging* 2018; **37**: 1488-1497 [PMID: 29870376 DOI: 10.1109/TMI.2018.2820120]

19 **Mardani M**, Gong E, Cheng JY, Vasanawala SS, Zaharchuk G, Xing L, Pauly JM. Deep Generative Adversarial Neural Networks for Compressive Sensing MRI. *IEEE Trans Med Imaging* 2019; **38**: 167-179 [PMID: 30040634 DOI: 10.1109/TMI.2018.2858752]

20 **Qin C**, Schlemper J, Caballero J, Price AN, Hajnal JV, Rueckert D. Convolutional Recurrent Neural Networks for Dynamic MR Image Reconstruction. *IEEE Trans Med Imaging* 2019; **38**: 280-290 [PMID: 30080145 DOI: 10.1109/TMI.2018.2863670]

21 **Kofler A**, Dewey M, Schaeffter T, Wald C, Kolbitsch C. Spatio-Temporal Deep Learning-Based Undersampling Artefact Reduction for 2D Radial Cine MRI With Limited Training Data. *IEEE Trans Med Imaging* 2020; **39**: 703-717 [PMID: 31403407 DOI: 10.1109/TMI.2019.2930318]

22 **Hsieh J,** Liu E, Nett B, Tang J, Thibault JB, Sahney S. A new era of image reconstruction: TrueFidelityTM - Technical white paper on deep learning imaging reconstruction. New York: General Electric Company, 2019: 1-14

23 **Boedeker K.** AiCE deep learning reconstruction: bringing the power of ultra-high resolution CT to routine imaging. Tochigi: Canon Medical Systems Corporation, 2019

24 **Kim K**, Wu D, Gong K, Dutta J, Kim JH, Son YD, Kim HK, El Fakhri G, Li Q. Penalized PET Reconstruction Using Deep Learning Prior and Local Linear Fitting. *IEEE Trans Med Imaging* 2018; **37**: 1478-1487 [PMID: 29870375 DOI: 10.1109/TMI.2018.2832613]

25 **Ouyang J**, Chen KT, Gong E, Pauly J, Zaharchuk G. Ultra-low-dose PET reconstruction using generative adversarial network with feature matching and task-specific perceptual loss. *Med Phys* 2019; **46**: 3555-3564 [PMID: 31131901 DOI: 10.1002/mp.13626]

26 **Xu J**, Liu H. Three-dimensional convolutional neural networks for simultaneous dual-tracer PET imaging. *Phys Med Biol* 2019; **64**: 185016 [PMID: 31292287 DOI: 10.1088/1361-6560/ab3103]

27 **Gong K**, Catana C, Qi J, Li Q. PET Image Reconstruction Using Deep Image Prior. *IEEE Trans Med Imaging* 2019; **38**: 1655-1665 [PMID: 30575530 DOI: 10.1109/TMI.2018.2888491]

28 **Whiteley W**, Luk WK, Gregor J. DirectPET: full-size neural network PET reconstruction from sinogram data. *J Med Imaging (Bellingham)* 2020; **7**: 032503 [PMID: 32206686 DOI: 10.1117/1.JMI.7.3.032503]

29 **Antholzer S**, Haltmeier M, Schwab J. Deep learning for photoacoustic tomography from sparse data. *Inverse Probl Sci Eng* 2019; **27**: 987-1005 [PMID: 31057659 DOI: 10.1080/17415977.2018.1518444]

30 **Waibel D,** Grohl J, Isensee F, Kirchner T, Maier-Hein K, Maier-Hein L. Reconstruction of initial pressure from limited view photoacoustic images using deep learning. In: Oraevsky A, Wang L, editors. Photons Plus Ultrasound: Imaging and Sensing. SPIE, 2018: 104942S [DOI: 10.1117/12.2288353]

31 **Hauptmann A**, Lucka F, Betcke M, Huynh N, Adler J, Cox B, Beard P, Ourselin S, Arridge S. Model-Based Learning for Accelerated, Limited-View 3-D Photoacoustic Tomography. *IEEE Trans Med Imaging* 2018; **37**: 1382-1393 [PMID: 29870367 DOI: 10.1109/TMI.2018.2820382]

32 **Deng H,** Wang X, Cai C, Luo J, Ma C. Machine-learning enhanced photoacoustic computed tomography in a limited view configuration. In: Yuan XC, Carney PS, Shi K, Somekh MG, editors. Advanced Optical Imaging Technologies II. SPIE, 2019: 111860J [DOI: 10.1117/12.2539148]

33 **Vu T**, Li M, Humayun H, Zhou Y, Yao J. A generative adversarial network for artifact removal in photoacoustic computed tomography with a linear-array transducer. *Exp Biol Med (Maywood)* 2020; **245**: 597-605 [PMID: 32208974 DOI: 10.1177/1535370220914285]

34 **Gao Y,** Wang K, An Y, Jiang SX, Meng H, Tian J. Non model-based bioluminescence tomography using a machine-learning reconstruction strategy. *Optica* 2018; **5**: 1451-1454 [DOI: 10.1364/OPTICA.5.001451]

35 **Guo L**, Liu F, Cai C, Liu J, Zhang G. 3D deep encoder-decoder network for fluorescence molecular tomography. *Opt Lett* 2019; **44**: 1892-1895 [PMID: 30985768 DOI: 10.1364/OL.44.001892]

36 **Zhang Z**, Cai M, Gao Y, Shi X, Zhang X, Hu Z, Tian J. A novel Cerenkov luminescence tomography approach using multilayer fully connected neural network. *Phys Med Biol* 2019; **64**: 245010 [PMID: 31770734 DOI: 10.1088/1361-6560/ab5bb4]

37 **Li DS,** Chen CX, Li JF, Yan Q. Reconstruction of fluorescence molecular tomography based on graph convolution networks. *J Opt* 2020; **22**: 045602 [DOI: 10.1088/2040-8986/ab76a5]

38 **Yoo J**, Sabir S, Heo D, Kim KH, Wahab A, Choi Y, Lee SI, Chae EY, Kim HH, Bae YM, Choi YW, Cho S, Ye JC. Deep Learning Diffuse Optical Tomography. *IEEE Trans Med Imaging* 2020; **39**: 877-887 [PMID: 31442973 DOI: 10.1109/TMI.2019.2936522]

39 **Cong W**, Wang G, Kumar D, Liu Y, Jiang M, Wang L, Hoffman E, McLennan G, McCray P, Zabner J, Cong A. Practical reconstruction method for bioluminescence tomography. *Opt Express* 2005; **13**: 6756-6771 [PMID: 19498692 DOI: 10.1364/OPEX.13.006756]

40 **Darne C**, Lu Y, Sevick-Muraca EM. Small animal fluorescence and bioluminescence tomography: a review of approaches, algorithms and technology update. *Phys Med Biol* 2014; **59**: R1-64 [PMID: 24334634 DOI: 10.1088/0031-9155/59/1/R1]**Footnotes**

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