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ABOUT COVER

Editor-in-Chief of *Artificial Intelligence in Medical Imaging*, Professor Xue-Li Chen is an expert in the field of biomedical photonics imaging as well as its application in early detection and accurate diagnosis of gastric cancer. Professor Chen has co-led the development of Cerenkov luminescence endoscope and further explored the application in early detection of clinical gastrointestinal tumors. Professor Chen has also developed the stimulated Raman projection tomography technology which can perform the volumetric imaging of single cells in a label-free manner. Professor Chen has served as the member of SPIE, OSA, IEEE, and as a committee member of the Branch of Contrast Technology in China Medicinal Biotech Association, the Nuclear Medicine Committee of Shaanxi Cancer Association, and the Shaanxi Society of Biomedical Engineering.

AIMS AND SCOPE

The primary aim of *Artificial Intelligence in Medical Imaging* (*AIMI*, *Artif Intell Med Imaging*) is to provide scholars and readers from various fields of artificial intelligence in medical imaging with a platform to publish high-quality basic and clinical research articles and communicate their research findings online.

AIMI mainly publishes articles reporting research results obtained in the field of artificial intelligence in medical imaging and covering a wide range of topics, including artificial intelligence in radiology, pathology image analysis, endoscopy, molecular imaging, and ultrasonography.

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EDITORIAL

Rising role of artificial intelligence in image reconstruction for biomedical imaging

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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

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.

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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.

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