Preface for a Special Issue of AUDT with AI in Medical Ultrasound

In recent years, the continuous development of AI technology has led to the emergence of many new ultrasound technologies based on artificial intelligence, greatly promoting the development of ultrasound medicine. Advanced technologies such as ChatGPT and 5G have ushered in a new era of innovation in the field of ultrasound medicine, offering new possibilities for digital intelligence.

The potential applications of ChatGPT in ultrasound have been discussed and hotly debated by Chinese scholars. This discussion has also been of great interest to our Editor-in-Chief, Ji-Bin Liu, who suggested a special issue on ultrasound AI and ChatGPT-related ultrasound applications, leading to the creation of this issue. Undoubtedly, ultrasound medicine will undergo significant upgrades and improvements, providing doctors with even more advanced tools and methods to aid in the diagnosis and treatment of diseases.

As ChatGPT comes online, the Advanced Ultrasound in Diagnosis and Therapy (AUDT) has collaborated with leading experts in the field of ultrasound medicine and artificial intelligence to release a special issue in both print and online formats. This special issue will focus on the application of AI, ChatGPT and 5G technologies in ultrasound medicine, and will feature review articles on the current status and trends in ultrasound medicine technology. We hope to provide leading-edge knowledge and useful information for both clinical researchers and basic scientists.

The Advanced Ultrasound in Diagnosis and Therapy (AUDT) is an open access journal in English with both online and printed publications which was created by the China-American Ultrasound Scholar Alliance. The journal covers various topics related to ultrasound technology, including advanced ultrasound imaging techniques, ultrasound-guided interventions, and the development of new ultrasound technologies. This special issue will introduce the application progress and prospects of AI in advanced ultrasound technologies, such as modality conversion, 3D/4D reconstruction, semi-supervised ultrasound video object segmentation (SUVOS), automated breast volume scanning (ABVS) and cloud handheld ultrasound system. Due to the large number of articles received in this special issue, some of them will be published in the upcoming issue.

We express our sincerest gratitude to all the members of the editorial board, journal reviewers, and authors for their diligent efforts in contributing to this journal and producing exceptional articles within a limited time frame. We also extend our appreciation to all the experts, scholars, and readers for their support and interest in this special issue of the journal. We welcome any feedback and comments on the content of this issue, which we hope will provide practical value and assistance to our readers.
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204 The Impact of Deep Learning on Ultrasound in Diagnosis and Therapy: Enhancing Clinical Decision Support, Workflow Efficiency, Quantification, Image Registration, and Real-time Assistance

Won-Chul Bang, Vice President, Yeong Kyeong Seong, Jinyong Lee
Ultrasound Image Generation and Modality Conversion Based on Deep Learning

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Abstract: Artificial intelligent (AI) based on deep learning has been used in medical imaging analysis for years. Improvements have been made in the diagnosis of various diseases with the help of deep learning. Multimodal medical imaging combines two or more imaging modalities, providing comprehensive diagnostic information of the diseases. However, some modality problems always exist in clinical practice. Recently, AI-based deep learning technologies have realized the modality conversion. Investigations on modality conversion have gradually been reported in order to acquire multimodal information. MRI images could be generated from CT images while ultrasound elastography could be generated from B mode ultrasonography. Continuous researches and development of new technologies around deep learning are still under investigation and provide huge clinical potentials in the future. The purpose of this review is to summarize an overview of the current applications and prospects of deep learning-based modality conversion of medical imaging.

Key words: Ultrasound image generation; Modality conversion; Deep learning

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Investigations of multimodal imaging have undergone decades of development and evolution since the 1970s, successfully realizing the inevitable transition from multimodal machine learning to multimodal deep learning. By enhancing machines' recognition and interaction capabilities across various modalities, multimodal machine learning has laid the groundwork for deep learning which has inherited the advantages of the former and also make significant improvements. The rapid development of multimodal deep learning has brought new opportunities for cross-modal medical image conversion.

With the rapid development of machine learning and deep learning, artificial intelligence (AI) based multimodality has progressed from the interaction of various modalities to the conversion of multimodality [1,2]. Multimodal medical imaging refers to the combination of two or more images formed by different imaging principles or devices, including ultrasound, X-ray, CT, MRI, PET, etc. Ultrasound imaging includes B-mode imaging, color/power Doppler imaging, contrast-enhanced ultrasound, and ultrasound elastography. A single modality imaging can only provide very limited diagnostic information, while multimodality can obtain wide-ranging information and provide comprehensive analysis about diseases. However, in daily clinical setting, not all patients are able and suitable to obtain clear diagnosis from some types of imaging exam. For example, there is a strong magnetic field effect for MRI and it is a contraindication for patients with implanted heart pacemakers, metal coronary stents, artificial joints, and other metal implants. Patients with claustrophobia cannot tolerate long-term narrow environment during MRI scans. Ultrasound examinations are flexible and more suitable for critically ill or postoperative patients who are bedridden for a long time. PET and MRI are expensive and not as easy to popularize and apply as ultrasound examinations. Contrast-enhanced ultrasound or ultrasound elastography cannot be used in some low-end devices (for example, portable ultrasound machine).
In recent years, many studies have reported that deep learning technology in AI field could transform one modality into another, achieving multimodal image conversion.

**Generating CT Images from MRI Images**

Radiation therapy is an important method of tumor treatment. Currently, CT is the baseline image modality for management of radiation therapy, providing the electron density map needed for dose calculation. However, there are limitations in CT that low soft tissue contrast exists and it produces ionizing radiation during the imaging process. MRI goes with better soft tissue imaging ability and no ionizing radiation, so that the study of generating CT images from MRI has important clinical value. With the popularity of MRI-simulated positioning devices, using MRI-only based planning in radiation therapy has gradually become a research focus [3]. According to different training models, the methods of generating CT images from MRI images can be divided into three categories: dictionary learning, random forest, and deep learning [4]. Using deep learning, researchers could quickly generate high-precision CT images, and the synthesized CT could provide the electron density information required by radiation therapy planning and dose calculation. The most commonly used deep learning method for MRI-only technology is the Generative Adversarial Network (GAN), which is currently mainly used for brain and pelvic areas [5].

**Generating MRI Images from CT Images**

Explorations about generating MRI images from CT images is relatively limited. As MRI maintains good soft tissue contrast ability, CT images generated MRI images can improve the automatic delineation of soft tissue organs in the abdomen based on the superior soft tissue information provided by MRI [6]. Jin et al. used GANs to convert brain CT images to brain MR images, and the synthesized images can effectively estimate the structures (such as brain vessels, gyri, and bones) in complex 2D brain slices [7] Feng et al. proposed a cross-modal imaging generation algorithm from CT to MRI on acute ischemic stroke by combining radiomics with GANs, and the results showed that the generated MRI images were very similar to the real MRI images, with precise lesion locations and similar lesion shapes to the real lesions, which would aid in getting prompt diagnosis and treatment for patients [8]. In the comparison of different deep learning models, research has been conducted using unsupervised network CycleGAN, supervised network Pix2Pix, and U-Net model to generate brain MRI images from CT images and to help locate the target lesion during radiation therapy. The results showed that the performance of supervised U-Net was better than unsupervised CycleGAN [9].

**Conversion of Different Sequences of MRI Images**

There were multiple imaging sequences in MRI. For example, T1-weighted MRI can clearly display anatomical structures, and T2-weighted MRI can highlight target lesion areas. However, there are still limitations such as high medical costs and long imaging times that can cause artifacts. It is common in clinical practice that patients may encounter problems of missing images of a certain imaging sequence. Deep learning could be used to generate T2-weighted MRI images from T1-weighted MRI images or to generate T1-weighted images from T2-weighted images. This is currently often used in the field of the brain [10-13]. Some studies have also attempted to synthesize multi-modal MRI images from a single MR image using GAN. For example, T1-weighted MRI was used as input and then T1c, T2, and Flair images were generated [13].

**Conversion of Different Ultrasound Modality**

There is limited research on modality conversion of ultrasound imaging. In early studies, fast simulation of ultrasound imaging was conducted from CT imaging by estimating ultrasound imaging parameters such as attenuation, reflection, scattering, transmission, and noise through weighted integration of adjacent regions along the ultrasound propagation path in CT imaging [14-16], thereby generating virtual ultrasound imaging to assist radiologists in learning and interpreting ultrasound imaging more quickly. In addition, it was reported that cycleGAN method was used to synthesize B-mode ultrasound images of skeletal muscles, which visually resemble real imaging. This method can be used to generate large annotated datasets for training deep neural networks for imaging segmentation tasks [17]. Similar studies have also been reported that GAN was used to synthesize intravascular ultrasound imaging [18]. Improving imaging resolution and making imaging scanners more portable are two major trends in ultrasound imaging research. However, improving imaging resolution inevitably requires more complex instrument components. The portable ultrasound scanners used in clinical practice currently are with low imaging quality, which could not meet the needs of most patients for ultrasound diagnosis. Studies have shown that imaging resolution of low-end ultrasound scanner could be improved with the help of deep learning, which indicates its valuable applications in improving
ultrasound imaging quality. Wang et al found that using GAN methods could improve the image quality of handheld ultrasound equipment [19].

The modes of ultrasound imaging mainly include B-mode imaging, color/power Doppler imaging, contrast-enhanced imaging, and ultrasound elastography. In recent years, a few studies have started to involve with the conversion between different ultrasound imaging modes, mainly focusing on the generation of ultrasound elastography imaging. There are the following bottlenecks for current ultrasound elastography: ① Due to the complexity of the imaging principle and the high cost of hardware and software, shareware elastography (SWE) function currently has only been implanted in high-end ultrasound equipment; ② On lesions located deeply in the body, significant degradation existed in the imaging quality of SWE due to the attenuation of acoustic radiation force pulses and detection pulses; ③ SWE is significantly operator dependent and there would be a long learning curve. The rapid development of multimodal deep learning technology provides a means to solve this problem. In early studies, researchers used end-to-end convolutional neural networks (CNNs) to directly reconstruct ultrasound elastography imaging from radiofrequency data [20]. More research was conducted based on generating ultrasound elastography imaging through deep learning from traditional B-mode ultrasound imaging. Kibria used a deep CNN to obtain rough but robust time delay estimates between two ultrasound images, and then obtained strain elastography (SE) imaging based on displacement information [21]. Recently, Zhang et al. proposed an automatic ultrasound elastography method based on the U-Net architecture, called AUE-net. This method extracts tissue features from B-mode ultrasound images of the thyroid and then transforms B-mode images into corresponding elastography images through a strain model. Finally, the strain imaging are reconstructed into corresponding SWE images. Ultrasound experts evaluated the thyroid elastography images generated with AUE-net and reported an average accuracy of 84.38%, indicating that a high-quality elastography images could be generated by the model [22].

In terms of SWE imaging synthesis, researchers have designed a deep fully convolutional neural network (DCNN) to synthesize SWE images from conventional ultrasound imaging of the prostate. The network can evaluate the echo patterns in B-mode ultrasound images and synthesize SWE images directly from B-mode ultrasound images. The researchers also found that the prostate-based model cannot be directly applied to thyroid elastography, and the network must be retrained for different organs [23]. Recently, in Zhou's research, B-mode imaging of breast lesions were used to generate SE imaging, which were named "virtual elastography". It was demonstrated that virtual SE showed similar diagnostic performance to real SE (Fig. 1) [24]. The model was applied to mid- to low-end ultrasound devices and combined with AI, improving the accuracy of mid- to low-end ultrasound in breast cancer diagnosis and screening, which has important scientific and clinical significance.

Prospects

In the era of rapid development of AI-based technology, the applications of cross-modal medical imaging based on deep learning is more and more extensive, and different modes of medical imaging methods possess their own advantages. For most diseases, multimodal imaging provides more accurate and comprehensive information in the assessment of diseases. Ultrasound elastography evaluates the stiffness of the breast mass, thus there is potential clinical significance of elastography for the diagnosis of benign and malignant mass. Contrast-
enhanced ultrasound is valuable in evaluating the degree of blood supply and vascularity of the solid tumors. However, it requires the accumulation of experience to accurately identify the contrast mode of malignant tumors. More and more clinicians are beginning to include elastography and contrast-enhanced ultrasound in preoperative examination. Nevertheless, in the actual clinical application, most of the patients are not able to acquire multi-modal imaging diagnosis. AI-based multi-modal conversion holds great potentials to solve the problem of insufficient clinical diagnosis caused by the absence of a certain imaging mode. At present, the research based on different mode transformation of ultrasonic imaging is still in its infancy, mainly focusing on mode transformation from B-mode ultrasound to ultrasonic elastography imaging. In the future, it is necessary to explore more technical methods to solve the problems in conversion of traditional ultrasound, contrast-enhanced ultrasound and ultrasound elastography, so as to improve the diagnosis of more diseases that are not sufficiently diagnosed by traditional ultrasound techniques.

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Conflict of Interest
The authors have no conflict of interest to declare.

Reference