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Application of Artificial Intelligence Technology in Radiotherapy to Delineate Endangered Organs

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Abstract: With the development of science and technology, artificial intelligence technology has been tried to be applied to all aspects of tumor radiotherapy, including respiratory motion prediction during simulated positioning, delineation of dangerous organs and tumor targets, and prediction of dose distribution. At present, clinical radiotherapy is mainly used in the automatic delineation of endangered organs, and artificial intelligence has demonstrated high accuracy in the delineation of dangerous organs, but there are also certain limitations. This article reviews the application and shortcomings of artificial systems in the automatic delineation of dangerous organs.
Keywords: Artificial Intelligence; Machine Learning; Radiation Therapy; Endangers Organs

1. Introduction

Since the concept of artificial intelligence was first proposed in 1956 [1], the development of artificial intelligence has gone through twists and turns, and now it has developed rapidly and has been widely used. AI technology has been initially applied to various fields of medical health, such as medical image analysis, medical pathology diagnosis, disease prediction, and research and development of new drugs. This article will focus on the application status and shortcomings of AI in the field of tumor radiotherapy.

2. Application of artificial intelligence in radiotherapy to automatically delineate dangerous organs

2.1 Head and neck endanger organs

Head and neck tumors, especially patients with nasopharyngeal carcinoma, have complex tumor target shapes, many surrounding dangerous organ structures, and most of the dangerous organs are small and irregular in shape, which is relatively difficult to delineate and delineate organs, and the delineation work will be more cumbersome and time-consuming. According to statistics, the manual delineation time of head and neck dangerous organs ranged from 2~3 h. The automatic delineation time is basically nearly 60 s/patient. Automatic sketching greatly improves work efficiency [2]. Some scholars developed an automatic delineation of dangerous organs software based on deep learning to automatically segment the dangerous organs of 185 nasopharyngeal cancer patients, and the results showed that the brainstem (0.896±0.03), eyeball (0.934±0.04), lens (0.836±0.07), larynx (0.87±0.04), mandible (0.913±0.04), oral cavity (0.928±0.03), mastoid (0.823±0.06), spinal cord (0.884± DICE coefficients were high in 0.07), parotid gland (0.851±0.05), temporomandibular joint (0.845±0.05), and optic nerve (0.689±0.1) all [3]. Some scholars used AccuContour software to automatically delineate 18 dangerous organs of the head and neck and compare them with the OARs manually sketched on the CT-MR fusion image, and the results showed that the smallest OARs of DSC were optic chiasm, the mean was 0.66, and the rest of the mean was greater than 0.85, the DSC of the pituitary gland was 0.871±0.113, the DSC of the thyroid gland was 0.969±0.019, and the largest HD value was the brain. The mean value was 10.1 mm, the pituitary HD value was 1.354±1.203, and the thyroid HD value was 3.266±0.232, which showed that there was a moderate positive correlation between HD and OARs size, and AccuContour software had good accuracy and repeatability for the delineation of head and neck dangerous organs [4]. However, the automatic delineation software shows certain limitations for the automatic delineation of small organs in the head and neck, so some scholars propose a 3D encoding-decoding network based on a classification model, which can divide the original CT image into 6 parts in the head and foot direction, and then put the classified different dangerous organs into the corresponding 3D encoding-decoding segmentation network. The DSC values of small volume structures such as crystal, optic nerve and optic chiasm automatically depicted by classification model and 3D segmentation network were 0.75, 0.84 and 0.82, respectively, indicating that the network has clinical use value [5].

2.2 The chest endangers organs

Zhang Song [6] pointed out that the clinical compliance rate of automatic sketching can meet the effectiveness of clinical sketching function if it reaches 85%. Studies have shown that generally DSC > 0.7 and HD<20 indicate a high degree of coincidence between the two structures [7]. Some scholars have discussed the feasibility of AI for automatic delineation of esophageal cancer, in which it takes at least 25 minutes to manually delineate all endangered organs, while the total time of the automatic delineation process is only 2~3 minutes, which greatly improves the efficiency of physicians. The similarity coefficient DSC values of the heart, liver, and spinal cord shape similarities of auto-sketching and manual sketching (gold standard) were all > 0.9, and the left lung > 0.86 and the right lung > 0.78 were higher than the standard of 0.7 [8]. Verification shows that there is good overlap and consistency between automatic and manual sketching. Some scholars used AccuContour software to automatically delineate the chest tumor danger organs, and the results showed that among the mean Hausdorff distances (standard deviation) of the lungs, heart and spinal cord, the largest was (22.31±4.50) mm in the right lung and the smallest was (3.17±0.80) mm in the spinal cord. The DSC values for OAR are ≥ 0.91, with DSCs as high as 0.98±0.01 in the left and right lungs, 0.92±0.02 in the spinal cord, and 0.91±0.03 in the heart [9]. However, some scholars [10] used deep convolutional networks to automatically segment the esophagus, and the results showed that the DSC was 0.726±0.094 and the HD95 was 8.714±10.588 mm, which was lower than that of other chest organs.

2.3 The abdomen endangers the organs

The main organs in the middle and upper abdomen are large-volume organs with small shape changes and clear boundaries, as well as organs with large shape variation and poor tissue contrast, such as stomach and pancreas. For structures with large shape variation and poor tissue contrast, such as the automatic segmentation of stomach and pancreas, Wang Linjing et al. [11] pointed out that automatic sketching software is difficult to meet basic clinical needs. However, studies have shown that the mean DSC of the stomach and pancreatic structures delineated by AccuContour software > 0.7, which coincides well with manual sketching [12]. A 2.5D UNet network model combining deep supervision of probability maps (CSNet) has been proposed to segment the pancreas, and experiments have shown that this method is superior to the traditional UNet segmentation method, and the DSC value can reach (83.74±5.27)% [13]. For large structures with clear boundaries such as liver, kidney and spinal cord, some scholars use three automatic sketching software for automatic sketching, all of which have good delineation effects, and their DSC mean values are greater than 0.8 [12]. Qin Wei et al. used AccuContour software to delineate the two gastric structures, and the results showed that the volume difference V% of normal stomach was (−1.82 ± 9.65%), the total position difference ΔL was (0.51 ±0.37) cm, and the shape consistency DSC value was 0.89 ± 0.04[14]. These data show that the AccuContour software has a good automatic sketching effect on normal stomachs. At the same time, the study also pointed out that the fullness of the stomach will affect the effect of automatic delineation, and for smaller stomachs, the automatic delineation results are not good. Some researchers evaluated the accuracy and efficiency of automatic segmentation of cascaded deep convolutional neural network VB-Net on the stomach and pancreas in 248 cases including enhanced CT and non-enhanced CT, and the results showed that the average DSC values of automatic segmentation of gastric and pancreas based on non-enhanced CT were 87.93% and 80.05%, respectively. The average DSC values of gastric and pancreatic auto-segmentation based on contrast-enhanced CT in the pancreatic phase were 89.71% and 84.79%, respectively. The VB-Net model is more accurate for the results of the gastric and pancreatic automatic segmentation model, and greatly improves the efficiency of organ segmentation [13].

2.4 The pelvis and other dangerous organs

Wang Jinyuan et al. [14] used Atlas template library to automatically delineate cervical cancer-threatening organs, and the results showed that the automatic delineation effect on the rectum was not good, and the DSC value was about 0.5. In order to solve the problem of automatic segmentation of organs with large differences in volume such as intestine and bladder, some scholars proposed a deeply expanded convolutional network (DDCNN), which evaluated the data of 278 rectal cancer patients and compared the performance of DDCNN with U-Net. The results showed that the average DSC value of DDCNN was 3.8% higher than that of U-Net. The mean DSC values of DDCNN for the bladder, left femoral head, right femoral head, bowel and colon were 87.7%, 93.4%, 92.1%, 92.3%, 65.3%, and 61.8%, respectively. The system exhibits excellent performance and faster speed for segmentation of the bladder, left and right femoral heads, colon, and intestine in 45 seconds per patient, but still lacks in automatic segmentation of the intestine[15]. Some studies have evaluated the feasibility of using 3D U-Net deep learning model to automatically segment pelvic tissue structure based on pelvic T2WI. The pelvic organs of 147 patients with prostate disease were automatically segmented, including prostate, bladder, rectum, bilateral seminal vesicles, urethra, bilateral obturator internal muscles and bilateral puborectal muscles. The results showed that the DSC of all structures of the pelvic cavity in the 3D U-Net model was > 0.90, among which the bladder was 0.96 (0.95, 0.97) and the rectum was 0.95 (0.92, 0.96). At the same time, there was no significant difference between the volume of pelvic structures segmented by the 3D U-Net model and manual labeling ($P>0.05$) [16]. The 3D U-Net DL model demonstrated high accuracy in the automatic segmentation of pelvic soft tissue structures shown by T2WI.

2.5 Opportunities and challenges

Although AI technology has demonstrated high accuracy in endangering automatic segmentation of organs, there are several unsolved challenges in applying AI to clinical practice. We highlight the following key issues: data volume, data quality, and performance metrics. The need to build large databases in the medical field is a key challenge. AI requires a large number of training samples to be useful in clinical practice. This means that deep learning frameworks need to be trained with enough representative examples to make them more accurate and reliable in practice. In addition, there are differences between the outline of the OAR itself or the sketcher. Another challenge is training an auto-sketch model on a biased dataset, such as a different annotation of the input image, which will definitely produce biased results. With the clinical application of AI, many data-related challenges have emerged, the biggest of which is the lack of a large number of high-quality labeled datasets.

Comparisons between the output of automatic contouring software are often difficult. Previous studies have used a variety of metrics to quantitatively assess the consistency of automation and expert profiles.

These challenges provide several opportunities to improve research possibilities in the field and in the future. For example, individual profile variability can be addressed by standardizing established expert consensus guidelines to systematize the profile of OAR, and contour variability within and between physicians will further improve the accuracy of existing DL models. Automated segmentation of OAR should facilitate the adoption of international consensus guidelines across centers to produce more favorable and standardized routine clinical practice.

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