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Research Article

Evaluation of a Clinical Acceptability of Artificial Intelligence Automatic Contouring: An Example of the use of Artificial Intelligence in Prostate Radiotherapy

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Abstract:

This study aimed to evaluate the usability and benefit of a new generation of auto segmentation, that automatically identifies organs and auto-contours them directly at CT simulator before creating prostate radiotherapy plans. The prostates of 10 patients were automatically contoured using the DirectORGANS auto-segmentation algorithm at the CT simulator. The CT scans were imported into the Eclipse treatment planning system for contouring. On the same CT image sets, the prostate was manually contoured by a group of five experienced physicians. MR-guided prostate contours were delineated using MRI images and used as a reference structure. The volumes of the prostate were measured, and the Overlap index (OI), Dice similarity index (DSC), and Volume difference (Dv) were calculated based on contours. The Kruskal-Wallis H test was performed with SPSS ($P<0.05$). MR-based contouring was used as a reference, and the OI, DSC, Dv, and contouring time results of users and artificial intelligence were analyzed accordingly. There was a significant difference in OI, DSC, and Dv between the results of users and artificial intelligence. The most significant difference between users, artificial intelligence, and MR-based contouring was contouring time ($p <0.001$). MR- based contouring was time-consuming. Artificial Intelligence's automatic contouring of the prostate required minimal modification.

1. Introduction

In recent years, with the increase in cancer cases, the number of patients receiving Radiation Therapy (RT) has also increased. Most cancer patients need RT during their disease [1]. Radiotherapy has become an important treatment technology applied after surgery [2]. A treatment plan is created for each patient who comes to the RT department. The most important part of the treatment planning process is to delineate the organ at risk and tumour contours. The increase in the number of patients increases the workload of doctors who delineate the OAR and tumour contours. Advances in technology and artificial intelligence help automate OAR and tumour contouring and reduce workload [3]. In many institutions, tumour and organs-at-risk contours are delineated manually; this is also costly and time-consuming.

Inter-observer variability prevents contouring with the same accuracy [4]. Recently, various automatic contouring methods have been created to solve these problems. However, all of these methods are not sufficient for physicians to obtain accurate contouring. One of the reasons is that most auto contouring results have been produced on CT images and is not optimal for the task of automated contouring. Automation is thought to help increase consistency. The first step in the workflow in radiotherapy is to delineate the contour of the tumour and organs at risk on the patient's CT image. Contouring on each CT image is a time-consuming process. In addition, OARs and tumour contours of the same patient contoured by different physicians may differ. By automatically contouring the organs at risk and tumours, it is thought that the efficiency of doctors increases and contour differences reduces by different doctors [5-8]. The accuracy of much different automatic contouring has been the subject of research. Recently, auto contouring methods have emerged that provide high accuracy in many anatomical regions [9-15]. For the prostate region, deep learning algorithms produce contouring results similar to expert manual segmentations for the bladder, femoral head, rectum, and SVs, but they are not good for the prostate [14].

There are different geometric metrics for evaluating contour variability and these are used as indicators of plan quality [16,17]. Popular geometric metrics such as the overlap index (OI), dice similarity coefficient (DSC), and volume difference (Dv) are available to evaluate contour uncertainty [18,19].

In study, the new generation of auto segmentation, (DirectOrgans, version VA30, Siemens, Erlangen, Germany) were selected. DirectORGANS is an algorithm that performs automatic contouring quickly and smoothly [20]. It provides the possibility to perform automatic contouring directly at the CT simulator and it is Deep Learning (DL) based contouring.

This study aimed to evaluate the usability of the new generation of auto segmentation, (DirectORGANS) that automatically identifies organs and auto-contours them before creating prostate radiotherapy plans. The geometric evaluation was performed by calculating the Dice Similarity Coefficient, (DSC), overlap index (OI), and volume difference (Dv) between users, artificial intelligence, and MR-based contouring, and the Kruskal-Wallis H test is applied to the results ($P<0.05$). In the first step of the study, the manual contours, which are delineated by experts Radiation Oncologists were compared with the prostate contours delineated automatically by artificial intelligence. And then, the manuel contours and AI contours were compared to MRI contours.

2. Material and Methods

10 prostate cancer patients were selected for this retrospective study**.** In this study, patients without hip implants were selected to avoid image artifacts. There was no age limit for the patients. All patients were selected from patients received radiotherapy. All patients' computed tomography (CT) simulations were in the supine position and had a scan thickness of 2 mm. The prostates were automatically contoured based on DirectORGANS (Siemens Healthineers AG, Germany) deep learning auto-segmentation at the CT simulator. The CT scans were imported into the Eclipse treatment planning system (TPS) (version 15.6) for contouring. On the same CT image sets, the prostate was manually contoured by a group of five experienced physicians. In addition, MR-guided prostate contours were delineated using MRI images and used as a reference structure. This imaging technique is remarkable because of high spatial resolution. Compared to CT, MRI provides better contrast in images of soft tissues, e.g. in the brain or abdomen, prostate.

The contouring time for each patient was measured. The volumes of the prostate were measured, and the Overlap index (OI), Dice similarity index (DSC), and Volume difference (Dv) were calculated based on contours.

$$OI = (V_{mr} \cap V_a) / V_a$$

$$DSC = 2\,(V_{mr} \cap V_a) / (V_{mr} + V_a)$$

$$D_v = (V_{mr} - V_a) / V_a$$

$$OI = (V_{mr} \cap V_m) / V_m$$

$$DSC = 2\,(V_{mr} \cap V_m) / (V_{mr} + V_m)$$

$$D_v = (V_{mr} - V_m) / V_m$$

In the formulas, Va represents the volume (cm^3) automatically contoured by the artificial intelligence, and Vm represents the volume (cm^3) manually contoured by the clinicians. In addition, Vmr represents the volume (cm^3) manually contoured using MR-based. The closer the OI index and the DSC index are to 1 and the D_V value to 0, the result means that the difference between the contours is not significant. The Kruskal-Wallis H test was applied to results with SPSS (P<0.05).

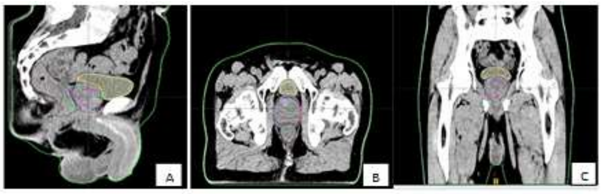

Figure 1. *The sagittal (A), transverse (B), and coronal (C) plane view of prostate contours determined by users and artificial intelligence*

3. Results and Discussions

In study, MR-based contouring was accepted as a reference and the prostate contours of users and artificial intelligence were analyzed accordingly. Figure 1 shows the prostate contours delineated by 5 users and artificial intelligence.

The comparison of OI, DSC, Dv, prostate volume, and contouring time results of the users, artificial intelligence, and MR-based contouring are shown in Table 1. The mean prostate volume was 50.9 ± 21.33 cc (ranged from 29.6 cc to 72.2 cc) for user 1 and 53.97 ± 22.69 ccs (ranged from 31.3 cc to 76.66 cc) for user 2 and 48.88 ± 18.06 cc (ranged from 30.8 cc to 66.94 cc) for user 3 and 54.54 ± 18.95 cc (ranged from 35.6 cc to 73.49 cc) for user 4 and 52.0 ± 21.5 cc (ranged from 30.5 cc to 73.5 cc) for user 5 and 49.98 ± 21.52 cc (ranged from 28.5 cc to 71.5 cc) for AI and 46.18 ± 17.92 cc (ranged from 28.3 cc to 64.1 cc) for MR-based contouring. The values of OI and DSC were calculated using these prostate volumes. The results of the study show that the values of OI and DSC are greater than 0.7, and Dv are less than 0.2. Figure 2, figure3, figure 4, figure 5, and figure 6 plot the OI, DSC, Dv, prostate volume, and contouring time of the prostate for users, artificial intelligence, and MR-based contouring. As a result of comparing users's datas with AI datas, there was no significant difference in OI between the results of users and artificial intelligence (p .211). No significant differences were found in DSC between the results of users and artificial intelligence (p. 001) and also there was no significant difference in D_v between the results of users and artificial intelligence (p. 0.099). There was no significant difference in prostate volume between the results of users and artificial intelligence (p. 0.994) The significant difference between users and artificial intelligence was contouring time (p **< 0.001).** Among them, the best contouring time was 0.15 for AI. As a result of comparing users and artificial intelligence according to MR, there was a significant difference in OI (p < 0.001). There was a significant difference in DSC (p < 0.001) and also there was a significant difference in Dv (p < 0.001). There was no significant difference in prostate volume between the results of users, artificial intelligence according to MRI based (p. 0.989). There was a significant difference in contouring time (p < 0.001). The longest contouring time was 7.01 for MR-based contouring and it was time-consuming.

Table 1. *Comparison of OI, DSC, Dv, prostate volume and contouring time for users, artificial intelligence, and MR-based contouring. Mean ± SD (min-max)*

	OI	DSC	DV	Volume	Time
User1	0.79 ± .096 (0.62-.094)	0.82 ± 0.05 (0.70-0.88)	0.12 ± 0.07 (0.03-0.27)	50.90 ± 21.33 (19.80-90.15)	3.41 ± 1.48 (1.26–6.49)
User2	0.7 ± 0.12 (0.55-0.87)	0.75 ± 0.07 (0.65-0.82)	0.13 ± 0.09 (0.02-0.26)	53.97 ± 22.69 (17.68-96.23)	2.71 ± 1.14 (1.42-4.44)
User3	0.73 ± 0.12 (0.49-0.88)	0.75 ± 0.10 (0.51-0.87)	0.08 ± 0.07 (0.01-019)	48.88 ± 18.06 (19.42-77.84)	1.67 ± 0.61 (1.18-3.15)
User4	0.78 ± 0.07 (0.67-0.88)	0.83 ± 0.04 (0.76-0.90)	0.21 ± 0.12 (0.07-0.38)	54.54 ± 18.95 (25.75-86.27)	2.30 ± 0.45 (1.45-3.16)
User5	0.81 ± 0.09 (0.70-0.96)	0.85 ± 0.03 (0.82-0.90)	0.15 ± 0.08 (0.04-0.27)	52.00 ± 21.50 (24.00-85.20)	2.01 ± 0.35 (1.30-2.50)
AI	0.80 ± 0.07 (0.69-0.90)	0.78 ± 0.06 (0.69-0.84)	0.13 ± 0.14 (0.01-0.45)	49.98 ± 21.52 (17.27-78.62)	0.16 ± 0.01 (0.14 – 0.16)
MRI based	1.00 ± 0 (1-1)	1.00 ± 0 (1-1)	0.00 ± 0 (0-0)	46.18 ± 17.92 (18.20-75.00)	4.95 ± 2.06 (2.21 -8.38)
P value*	.211	.001	0.990	0.994	< 0.001
P value**	< 0.001	< 0.001	< 0.001	.989	< 0.001

Kruskal Wallis
*(According to the comparison of users and AI)
** (According to the comparison of users and AI to MRI)

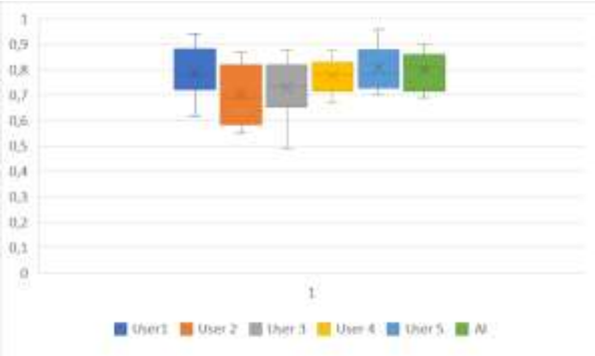

Figure 2. *The overlap index (OI) for users, artificial intelligence to MR-based contouring.*

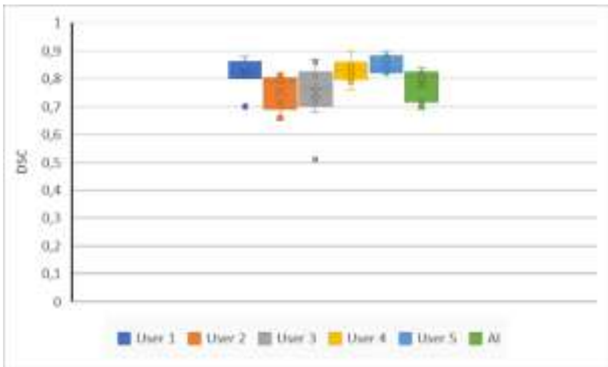

Figure 3. *The dice similarity coefficient (DSC) for users, artificial intelligence to MR-based contouring.*

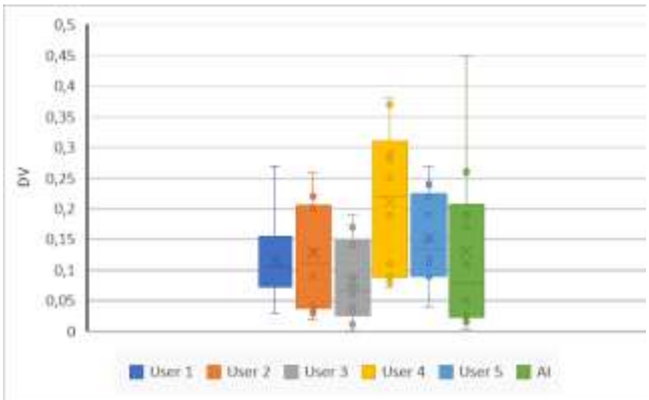

Figure 4. *The Volume difference (Dv) for users, artificial intelligence to MR-based contouring.*

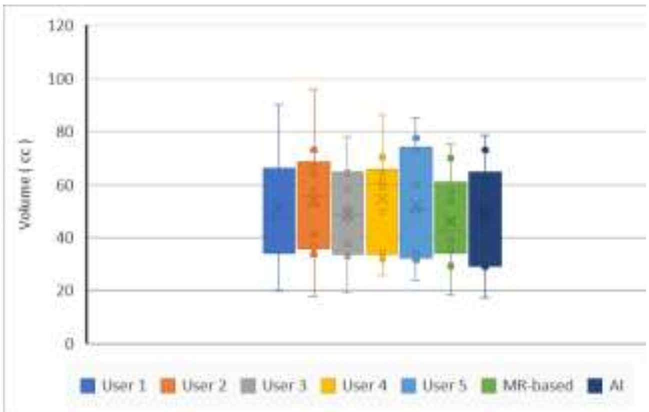

Figure 5. *The tumour volumes for users, artificial intelligence to MR-based contouring*

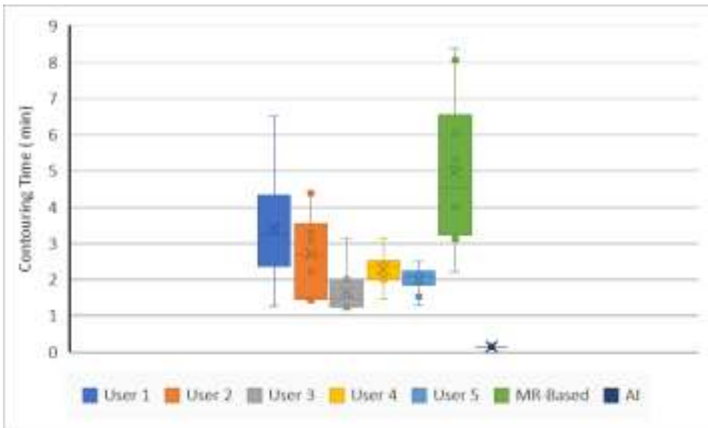

Figure 6. *The contouring time for users, artificial intelligence to MR-based contouring.*

This study was a prostate contour comparison between users, artificial intelligence, and MR-based contouring. As a result of comparing users's datas with AI datas, this study show that automatic contouring is similar to a clinician's manual contouring prostate, and greatly saves the physician's working time.

The accuracy of organ at risk and tumour contour often affects the dose distribution in radiotherapy and then impacts the treatment quality ultimately [21]. With the development of science and technology, automatic contouring has also been continuously improved. Due to the high accuracy of automatic contouring technology, physicians use it for clinical purposes with only minor modifications, reducing unnecessary workload for clinicians. In addition, it increases treatment efficiency. In study, the contouring time varies between users from about 1.5 minutes to 3 minutes. Due to differences in experience and expertise among doctors, contouring times vary. In addition, MR-based contouring was performed for longer periods such as 7 minutes. Deep learning automatic contouring was usually about 9 s. Automatic contouring time differs due to different software and different organs. There is so many different artificial intelligence that contour in a very short time [8]. The deep learning auto-segmentations is a model established by artificial intelligence. Therefore, it saves a lot of time.

For AI segmentation, OI values indicate an optimal agreement (mean>0.80 and SD<0.07) and DSC value (mean>0.78 and SD<0.06). The results of prostate delineation with users in prostate cases show that the values of OI and DSC are greater than 0.7, and Dv are less than 0.2. According to the OI and DSC results from deep learning auto-segmentations and users, the delineation results of the prostate are relatively close. Liu et al. reported a DSC value of 0.85 for 140 prostate cases and a DSC value of 0.88 for 10 prostate cases [22]. Ghavami et al. reported a DSC value of 0.89 ± 0.03 for prostate segmentation based on 232 magnetic resonance (MR) [23]. Wang et al. reported a DSC value of 0.855 ± 0.039 on their institutional datasets and 0.881 ± 0.047 on the PROMISE12 (Prostate MR Image Segmentation 2012) dataset [24]. This study's DSC values were lower than these studies.

As a result of comparing users and artificial intelligence according to MR, there was a significant difference between the results. The users and artificial intelligence performed the prostate contouring on tomography images. It is more difficult to contour the prostate on CT images than on MRI. Compared to CT, MRI provides better contrast in images of soft tissues, e.g. in the brain or abdomen, prostate. So, MR-based measurement was taken as reference. MRI images allow better visualization of prostate borders and more consistent contouring of the prostate. Accordingly, there was a significant difference between the contours drawn according to MRI and the others.

However, most prostate radiotherapy treatments are performed on CT simulation images [25-28]. It is thought that doctors start to creat the treatment plan without checking the prostate contour through deep learning auto-segmentations that contour on MR images. Some examples are reported in the literatüre [29-31].

4. Conclusions

DirectOrgans auto segmentation is useful tool for prostate contouring clinically. It is thought that there is need to clinicians review and confirm prostate volume using MRI before the treatment plan. It is more correct to use it after minimal modification. Artificial intelligence demonstrated its value for automated contouring of prostate volumes to save time. Artificial intelligence-based contouring showed important benefits in time-sparing combined with an improved inter-and intraobserver contouring variability.

Author Statements:

- **Ethical approval:** The conducted research is not related to either human or animal use.
- **Conflict of interest:** The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper

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- **Data availability statement:** The data that support the findings of this study are available on request from the corresponding author. The data are not publicly available due to privacy or ethical restrictions.

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