White paper

DirectORGANS 2.0

The world's first contours generated by a CT simulator – Technical principles and clinical evaluation

Lisa Kratzke, Dr. Nilesh Mistry, Dr. Christian Möhler,
Annie Bruder, Siemens Healthineers
Allison Müller, Dr. med. Thomas Weissmann,
Dr. med. Sina Mansoorian, Dr. med. Florian Putz,
University Hospital Erlangen, Germany

siemens-healthineers.com/radiotherapy

Courtesy of Leopoldina Hospital, Schweinfurt, Germany, Courtesy of Erlangen University Hospital, Germany
Cinematic VRT is for illustration purposes only. This feature is not part of DirectORGANS.

SIEMENS Healthineers

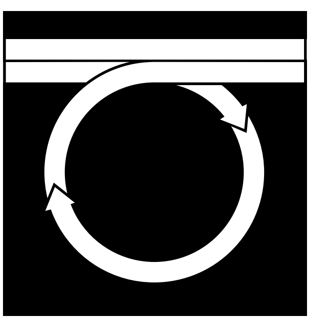
Table of contents

Key takeaways

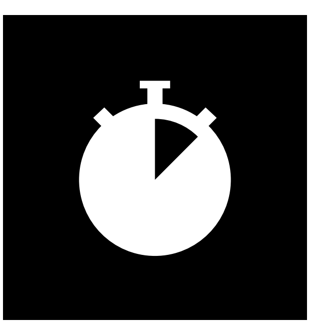
to understand DirectORGANS

Why a new autocontouring solution?
The quality of computer generated contours is significantly impacted by the input image quality, especially in the presence of artifacts, poor image statistics (i.e. increased noise), or poor contrast. All these factors can negatively impact relevant image features and may lead to suboptimal quality of the autocontouring [1] [2].

As a result, users spend a significant amount of time editing those organs-at-risk (OAR) contours – sometimes to a point that the potential benefits of autocontouring in terms of time saving may be completely lost.



How does DirectORGANS work?
In order to solve the problem at hand, it is necessary to provide the autocontouring solution with optimized input. For this reason, DirectORGANS (Optimized Reconstruction based Generative Adversarial Networks) employs an optimized reconstruction that is used as a standardized input to the Deep Learning based autocontouring algorithm. Both processes, image optimization and automatic contouring, are embedded into the CT simulator enabling results as part of the image acquisition.



What is the benefit?
By leveraging Artificial Intelligence (AI) to generate OAR contouring directly at the CT simulator, DirectORGANS provides consistent, standardized, high quality, contoured images that are ready as an output of the CT simulation process. This solution enables time efficient OAR contouring as part of the standard CT acquisition, freeing up staff to spend more time for other tasks.

Importance of autocontouring

In the last couple of years, not only the cancer incidence rates have increased, but also the amount of patients receiving radiation therapy (RT). Up to two thirds of all the patients with cancer will need RT treatment during the course of their disease [3].

Increase in cancer cases and their costs [4]

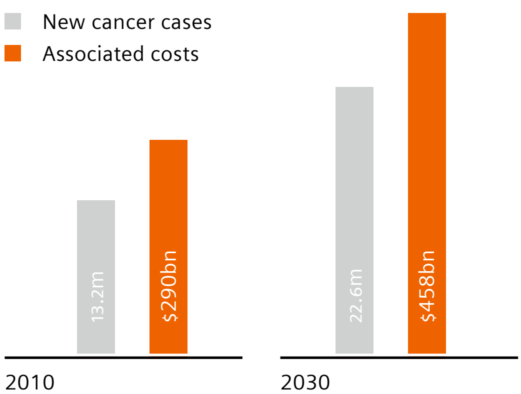


Fig. 1.1 Cancer statistics and incidence predictions

Percentage of cancer patients receiving radiation therapy [3]

Each patient arriving at the RT department requires a treatment plan. Contouring the organs-at-risk is the necessary first step in the process of treatment planning after the CT acquisition. Therefore, the increase in the number of patients puts significant pressure on radiotherapy staff responsible for consistent OAR contouring results. Advances in technology and AI can help automate repetitive tasks such as OAR contouring and reduce workload. The automation may help in increasing consistency while achieving better efficiency.

Challenges with OAR contouring

In many institutions, organs-at-risk are contoured manually; as a result valuable staff resources are tied up, turning OAR contouring into a cost and time intensive task. In addition, inter-observer variability can make it difficult to achieve consistent contouring results and operators need to be trained on common contouring guidelines. Considering staffing issues such as high turnover, consistent OAR contouring still is a problem in many institutions.

In the last decade, various autocontouring solutions have been introduced to address these challenges. However, the results may not be clinically useful for the RT professionals leading to significant editing or re-doing the contours. One of the reasons is that most autocontouring results have been produced on CT images optimized for human perception and may not be optimal for the task of automated contouring. However, the optimization of images is performed for a specific need in the clinic and introducing a new optimized reconstruction for the task of autocontouring may conflict with the original intent.

Fig. 1.2 Opportunities in OAR contouring

DirectORGANS supports RT professionals addressing contouring needs and workflow efficiency

To overcome the challenge of clinical workflow and simultaneously enable automated contouring we introduce DirectORGANS. DirectORGANS is the first integrated solution making OAR contouring a part of the acquisition task. The algorithm enables a fast and seamless workflow – not requiring manual data transfer, e.g. to a contouring workstation.

Additionally, we also integrate the process of optimized image reconstruction for the task of autocontouring. Hence, in clinical routine, no adaption of the workflow is needed. Research shows that up to one hour can be saved for the contouring of the organs-at-risk [5].

The DirectORGANS algorithm

DirectORGANS was developed to provide contoured images directly at the CT simulator.
Two core elements – optimized reconstruction and Deep Learning (DL) based contouring – lay the foundation for this technology.

One of the challenges of traditional autocontouring is the quality of the input images. Therefore, image optimization is a key step in order to provide consistent, high quality contours. Figure 2.1 illustrates the differences between an image optimized for the human and an image optimized for a machine: one of the keys to obtain consistent quality contours is to provide the algorithm with as much information as possible. Artifact reduction, higher spatial resolution are examples of ways to increase the amount of relevant information for the machine, however, increased spatial resolution leads to several challenges in the clinic. For example: increased z-resolution for the same coverage means increased workload for contouring and increased in-plane spatial resolution may lead to increased noise in the image – both features that are not desirable in the clinical situation.

Image designed for DirectORGANS

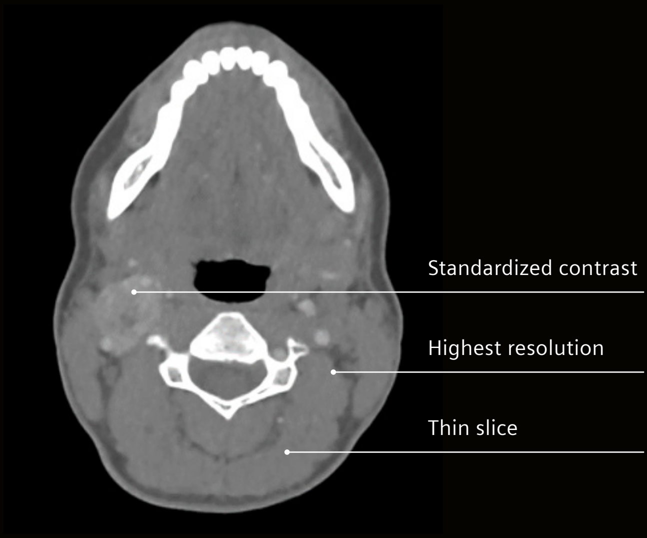


Image designed for RT professionals

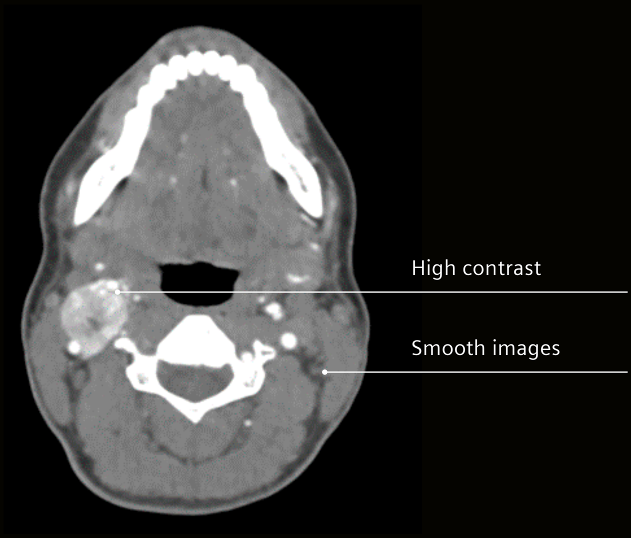


Fig. 2.1 Example of image designed for DirectORGANS (left) and RT professionals (right)

Courtesy of Radiology Department, Hospital Particular de Viana do Castelo, Viana do Castelo, Portugal

DirectORGANS is available for the most relevant cancer sites for External Beam Radiation Therapy (EBRT) such as brain, head & neck[1], breast, lung, abdominal and prostate (figure 2.2). Additionally, we offer advanced packages for the heart and the lung. Cardiac substructure[2] segmentation enables research in the field of cardiac toxicity. Contouring for the ribs and the lung substructures enables tailored treatment plans that minimize the risk of treatment-induced rib fractures [6].

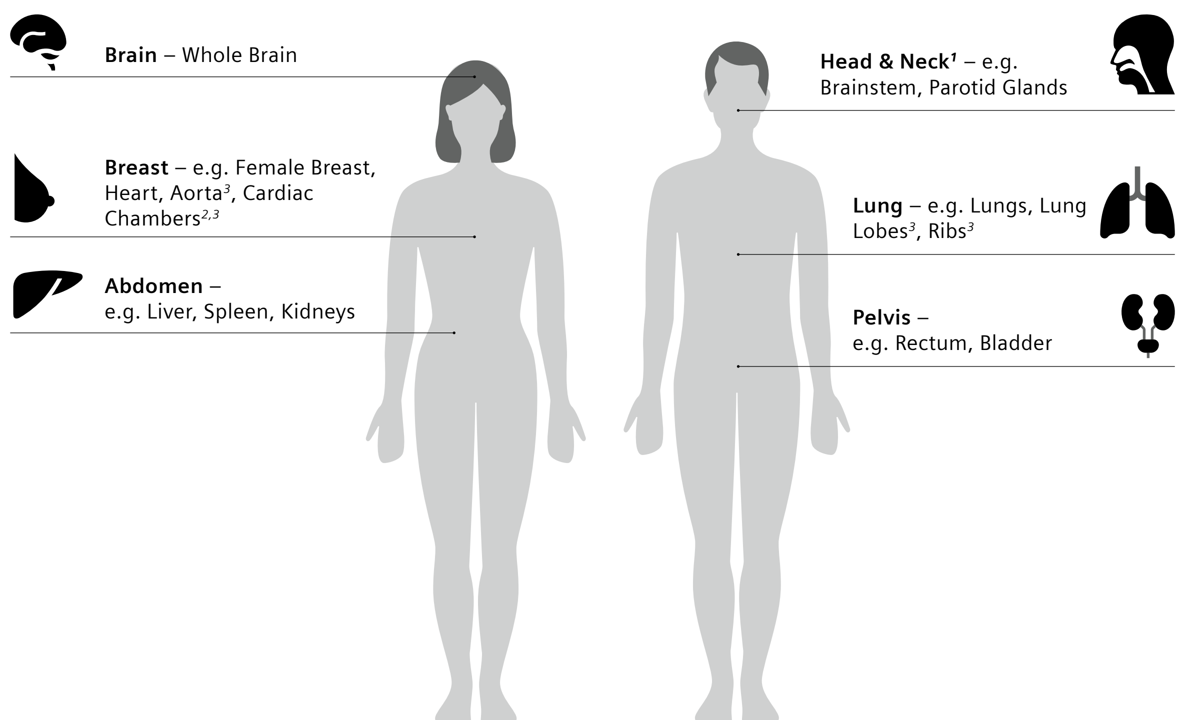


Fig. 2.2 Examples of contours generated by DirectORGANS and DirectORGANS Advanced (Software Version VA30)

[1] *Atlas-based*
[2] *MSL (marginal space learning) based*
[3] *Optional, DirectORGANS Advanced*

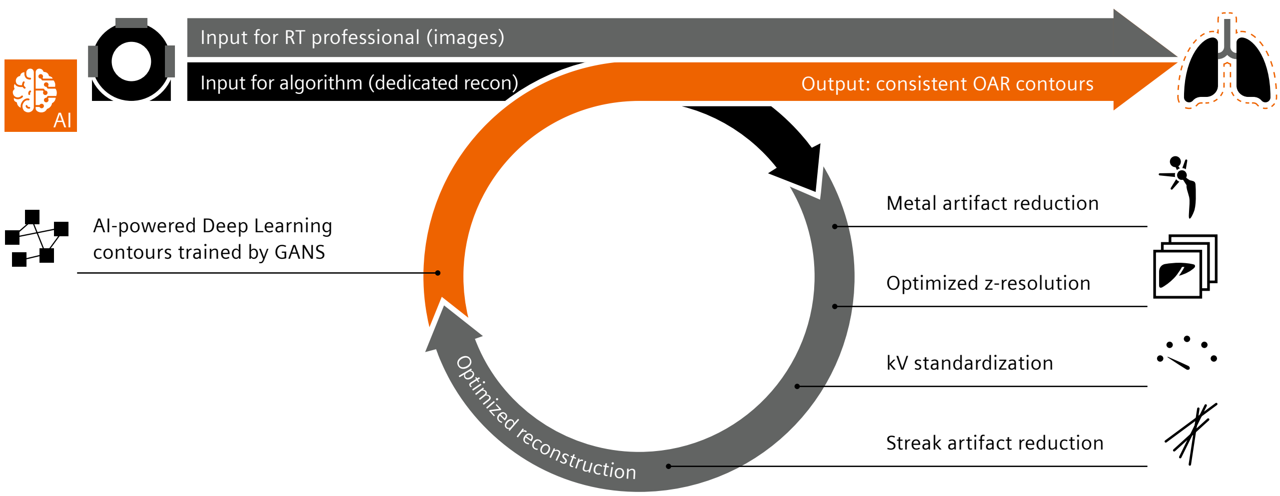


Fig. 2.3 Functional steps of the DirectORGANS algorithm

a) DirectORGANS in clinical routine

The acquired data is reconstructed in two parallel tracks: One to meet the requirements of human operators, i.e. with the individually preferred reconstruction parameters ("Input for RT professional" arrow in figure 2.3). The other one to provide images that are optimized for autocontouring by the CT simulator ("Input for algorithm" arrow in figure 2.3). Images optimized for the task of autocontouring have the highest possible information with the highest resolution, standardized contrast and minimized artifacts to enable consistent high-quality contours (see figure 2.1). Leveraging Deep Learning, the contours are generated based on the optimized images (orange arrow in figure 2.3). In the next step, the image designed for the RT professional and the contours are fused (figure 2.4). The resulting contoured image will be used for further treatment planning. The creation of the contours is explained in detail in the following.

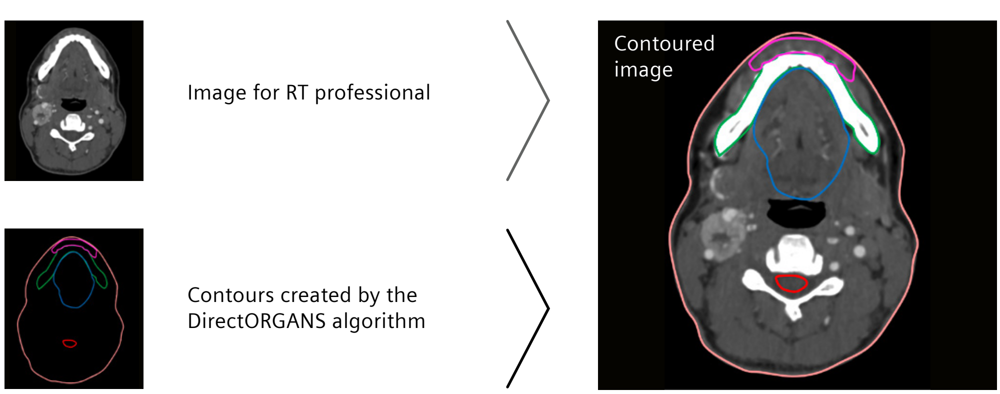


Fig. 2.4 The contours created by the DirectORGANS algorithm and the image optimized for human consumption are combined.
Courtesy of Radiology Department, Hospital Particular de Viana do Castelo, Viana do Castelo, Portugal

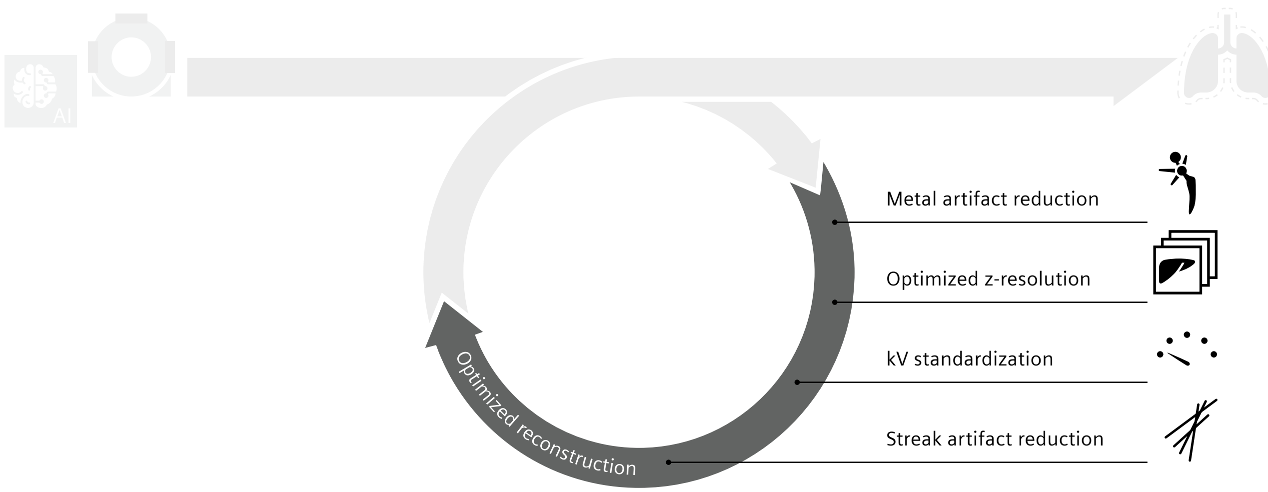


Fig. 2.5 Optimized reconstruction

Optimized reconstruction (OR)

CT imaging is a highly accurate and quantitative imaging modality that allows to obtain precise information about the tissue density distribution of the patient within a few seconds of scanning. Nevertheless, there are sources of artifacts that make the images less quantitative than desired. That is the reason why an optimized reconstruction is performed in the background prior to the creation of the contours (figure 2.5). One element of the optimized reconstruction is reducing metal artifacts. These are caused by the presence of high density objects such as implants, seeds, or fillings. Furthermore, noise and streak artifacts, e.g. from beam hardening, are corrected.

DirectORGANS uses a consistent slice thickness and slice increment for the optimized image reconstruction. kV standardization enables departments to leverage different kV settings for different patient sizes, ages and indications, while still generating consistent contours. That means DirectORGANS is capable of handling different scans independent of the selected kV. The optimized reconstruction of DirectORGANS enables an integrated way of generating images optimized for the contouring task without the need to change the existing workflow.

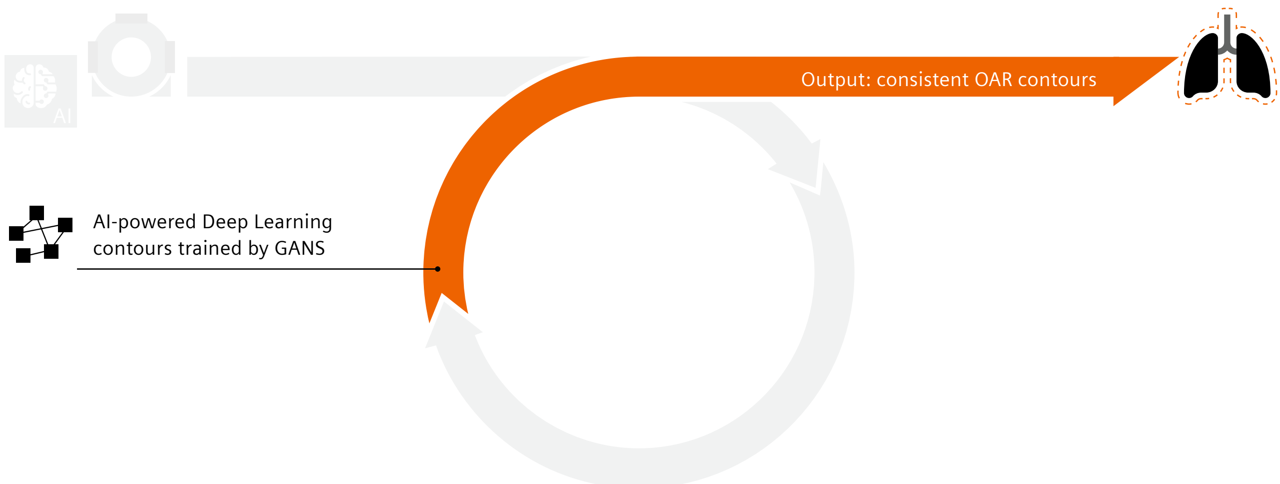


Fig. 2.6 Deep Learning Contouring

Deep Learning based contouring

Following the reconstruction, the optimized images are used to create the contours (figure 2.6). This process is based on a two step approach as can be seen in figure 2.7. First, the target organ region in the optimal input image is extracted using a Deep Reinforcement Learning trained network (DRL) [7]. The result is a cropped image with the target organ region. In the second step, the cropped image is used as input to create the contours. This step is based on a Deep Image-to-Image Network (DI2IN) [8]. The DI2IN was trained to its optimal performance in the Siemens Healthineers AI environment. The training process of the DI2IN is explained in the following section[1].

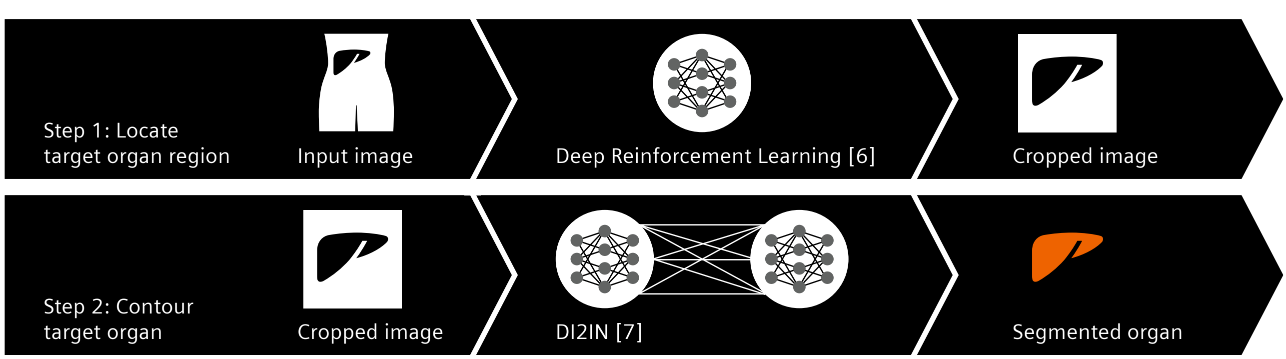


Fig. 2.7 Two step algorithm for DL based contouring

[1] *Please note – the algorithm is not self-learning. Your data is not used for further training.*

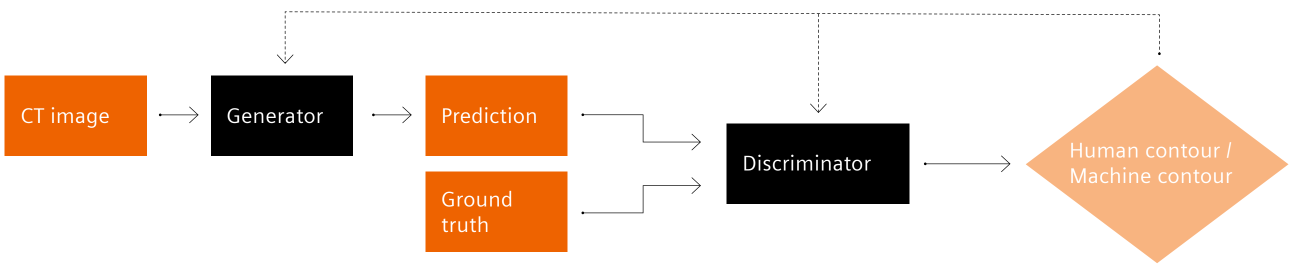


Fig.2.8 Adversarial training scheme

b) Training of the DirectORGANS algorithm

The DirectORGANS algorithm was trained leveraging Deep Learning technology. Deep Learning uses a multi-layer neural network that enables unsupervised learning for a specific task. Typically, the DL algorithm needs a large number of datasets to be trained.

To learn how to perform the organ segmentation, a Deep Image-to-Image Network is employed. It consists of a convolutional encoder-decoder architecture combined with a multi-level feature concatenation. An adversarial network – a so called Generative Adversarial Network (GAN) – is selectively used to regularize the training process of DI2IN by discriminating the prediction of the DI2IN from the ground truth (figure 2.8). The model is selected in the epoch with the best performance on the validation set. A GAN uses two networks that compete against each other during the training process. The first network – the generator – tries to emulate a human drawn contour while the second network – the discriminator – tries to discriminate the prediction of the first network from the ground truth (human drawn contour). The information is then fed back to the respective networks.This iterative process ensures that during the training of the networks, the machine generated contours become virtually indistinguishable from the human generated contours. For algorithm training, CT datasets were obtained for each body region from various radiation therapy and radiology departments in Europe and America. Ground-truth segmentations were manually generated on these CT datasets by a team of experienced annotators overseen by radiation oncologists or radiologists. For this process, a consistent annotation protocol was set up beforehand based on widely accepted consensus guidelines such as the ones published by the Radiation Therapy Oncology Group (RTOG). The organ models were then trained with pairs of CT data and the corresponding standardized ground-truth segmentation.

Clinical evaluation of DirectORGANS

Methods

DirectORGANS proposes to be a time-efficient OAR autocontouring solution providing consistent and high-quality contours. To assess the quality and clinical applicability, DirectORGANS was evaluated in collaboration with the Radiation Therapy Department of University Hospital Erlangen in Germany.

For the evaluation of DirectORGANS, a set of organs was selected to cover the most relevant cancer sites treated with EBRT:

- Head & Neck
- Breast
- Thorax
- Pelvis
- Abdomen

With the goal of evaluating time savings and clinical usability, three physicians or 'human annotators' manually contoured clinical images from 50 patients. These 50 patients were also automatically contoured using i) DirectORGANS, ii) an atlas-based solution from vendor A, and iii) a model-based solution from vendor B. Based on the number of patients, the number of OARs for each patient, and the different body regions, a total of 2,040 organs-at-risk structures were generated. Each resulting OAR was then evaluated by the three physicians in a blinded study barring their own manually drawn contour.

Step one – Evaluation of the quality (clinical usability)
A blinded setup was used to administer a 'Turing test' to evaluate the quality of the contours. Each human annotator acted as a 'reader' and rated the quality of the organ contours generated by the other two human annotators and the three different autocontouring solutions.

The clinical usability of the OARs was rated by the readers using a 4-point scale to determine the quality of the contours. The 4-point scale is as follows:

4 – clinically usable,
3 – usable after minor edits,
2 – usable after major edits,
1 – must redo.

Additionally, the readers documented cases where organs were not available either as 'contour missing' or as 'whole patient case failed'.

Step two – Evaluation of time savings
The time required for manual contouring of the different organs was captured for each 'human annotator.' This process allowed the use of manual contouring tools available in the contouring software used in the clinic, including interpolation.

Manual edits and corrections were made to the automatically generated contours by the physicians to make them clinically acceptable. If OARs were missing, manual delineation was required using the available contouring software.

Total time to generate clinically usable contours was compared with the following:

- total time to adapt the contours generated by DirectORGANS,
- total time to adapt the contours generated by contouring solution from Vendor A,
- total time to adapt the contours generated by contouring solution from Vendor B,
- and the mean time taken by the three human annotators for manual contouring.

Results & discussion

The objective of the evaluation is to assess the clinical usability and the associated time savings of DirectORGANS.

Figure 3.1 illustrates the quality of the contours for all the treatment sites. The study shows that about 80% of the cases generated by DirectORGANS and the physicians are clinically usable directly or with only minor edits, whereas it is about 40% for the solutions by vendor A and B.

When individual body sites were analyzed, the head and neck contours generated by DirectORGANS were rated lower than the physicians' contours, potentially because they were atlas-based. For the remaining body regions, the physicians involved in evaluating the clinical usability were not able to distinguish between the physician-generated contours and DirectORGANS-generated contours.

In the second part of the evaluation, the time required to generate the full set of clinically usable OARs was analyzed. Figure 3.2 shows the average contouring time per patient. The average time saved compared to the manual contouring is 11:24 minutes for DirectORGANS, 5:01 minutes for vendor A, and 5:52 minutes for vendor B.

With the consistent starting point (80% clinically usable contours), the use of DirectORGANS leads to significant time-savings compared to fully manual contouring. The time required to edit the contours from vendor A and B is substantially higher, partly due to missing OARs that required manual delineation. It is worth noting that the time-savings between different body regions vary based on the different numbers of OARs, different contouring tools available, and that smaller organs such as the kidney require less time than larger organs such as the lung.

Average rating of contours

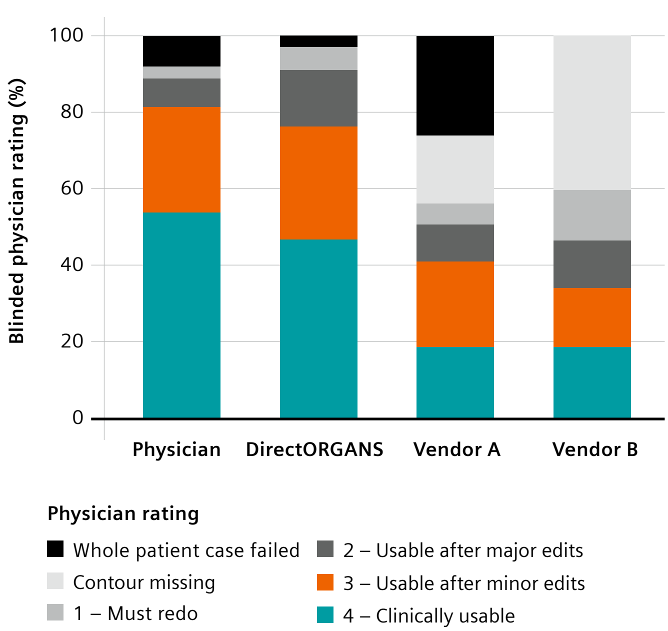


Figure 3.1
Average rating of contours

Average contouring time per patient in min

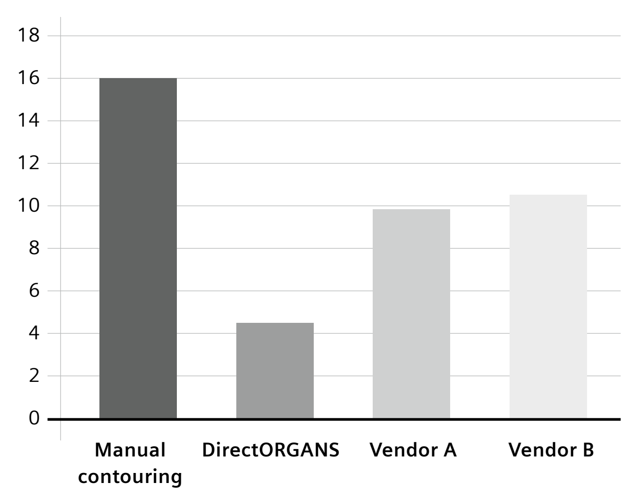


Figure 3.2
Average contouring time per patient in min

Conclusion

DirectORGANS leverages the power of an optimized image reconstruction and deep learning to streamline OAR contouring directly at the CT simulator. This new solution may help to reduce unwarranted variations with contours that provide a consistent starting point for radiation therapy planning with 80% of the contours rated to be clinically usable without manual interaction or minor editing. By design, DirectORGANS enables a fully automated workflow requiring no additional workstation for the OAR contouring.

This potentially leads to fewer errors originating from the application configuration or operation. As a result, on average it saves between 11–12 minutes for cases processed at the University Hospital in Erlangen. However, these times depend on several factors, such as the number of OARs used in the clinic, and clinical definitions for each OAR, and are highly dependent on the personnel involved. The results from DirectORGANS are inde-pendent of the user and hence provide mconsistent results. With DirectORGANS, OAR contouring becomes an integrated part of the standard CT acquisition.

The potential financial value of DirectORGANS:

Examples of time savings[1]

16.1 min

Manual OAR contouring
Average time spent:
16.1 min / clinical site

4.7 min

DirectORGANS (incl. review)
Average time spent:
4.7 min / clinical site

Average time savings

Ø11.4 min

Potential time savings

89.7 working days

- Spend more time with patients
- Reduce over hours
- Invest in education

Based on an assumption of:

- 252 working days per year[2]
- 15 patients per day
- 11.4 minutes saved on average per case

[1] Clinical data provided by Erlangen University Hospital
[2] http://www.joursouvres.de/en/joursouvres_joursferies_2020.
The statements by Siemens Healthineers' customers described herein are based on results that were achieved in the customer's unique setting. Since there is no "typical" hospital and many variables exist (e.g., hospital size, case mix, level of IT adoption) there can be no guarantee that other customers will achieve the same results

References

[1] WU, X., et al. Knowledge-based auto contouring for radiation therapy: Challenges in standardizing object definitions, ground truth delineations, object quality, and image quality. International Journal of Radiation Oncology Biology Physics, 2017, 99. Jg., Nr. 2, S. E740.
[2] Cheung CW, Leung KY, Lam WW, et al. Application of Model-based Iterative Reconstruction in Auto-contouring of Head and Neck Cases. Scientific Informal (Poster) Presentation at: LL-ROS-TH Radiation Oncology and Radiobiology Lunch Hour CME Posters; RSNA 2012 Nov 29; arXiv:1707.08037 [cs.CV] Chicago, IL.
[3] ATUN, Rifat, et al. Expanding global access to radiotherapy. The lancet oncology, 2015, 16. Jg., Nr. 10, S. 1153-1186.
[4] American Cancer Society, www.cancer.org
[5] DAS, Indra J.; MOSKVIN, Vadim; JOHNSTONE, Peter A. Analysis of treatment planning time among systems and planners for intensity-modulated radiation therapy. Journal of the American College of Radiology, 2009, 6. Jg., Nr. 7, S. 514-517.
[6] NAMBU, Atsushi, et al. Rib fracture after stereotactic radiotherapy for primary lung cancer: prevalence, degree of clinical symptoms, and risk factors. BMC cancer, 2013, 13. Jg., Nr. 1, S. 68.
[7] GHESU, Florin-Cristian, et al. Multi-scale deep reinforcement learning for real-time 3D-landmark detection in CT scans. IEEE transactions on pattern analysis and machine intelligence, 2017, 41. Jg., Nr. 1, S. 176-189.
[8] YANG, Dong, et al. Automatic Liver Segmentation Using Adversarial Image-to-Image Network. U.S. Patent Application Nr. 15/877,805, 2018.

Siemens Healthineers Headquarters
Siemens Healthcare GmbH
Henkestr. 127
91052 Erlangen, Germany
Phone: +49 9131 84-0
siemens-healthineers.com

Legal Manufacturer
Siemens Healthcare GmbH
Henkestr. 127
91052 Erlangen, Germany

Published by Siemens Healthcare GmbH · Online · 10183 0221 ·