White paper

DirectORGANS

The world's first contours generated by a CT simulator – Motivation and technical principles

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

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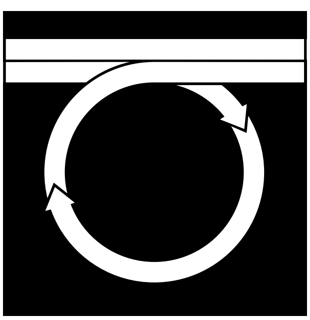
Key takeaways

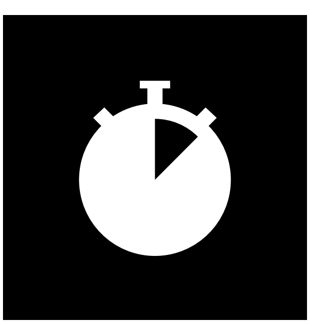
to understand DirectORGANS

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]

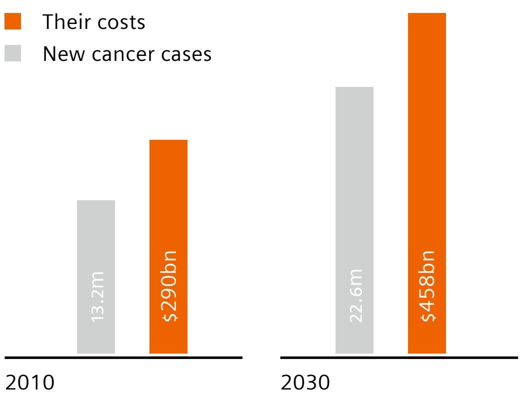


Fig. 1.1 Cancer statistics and incidence predictions

Percentage of cancer patients receiving radiation therapy [3]

Up to 2/3

of cancer patients receive radiation therapy.

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. 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.

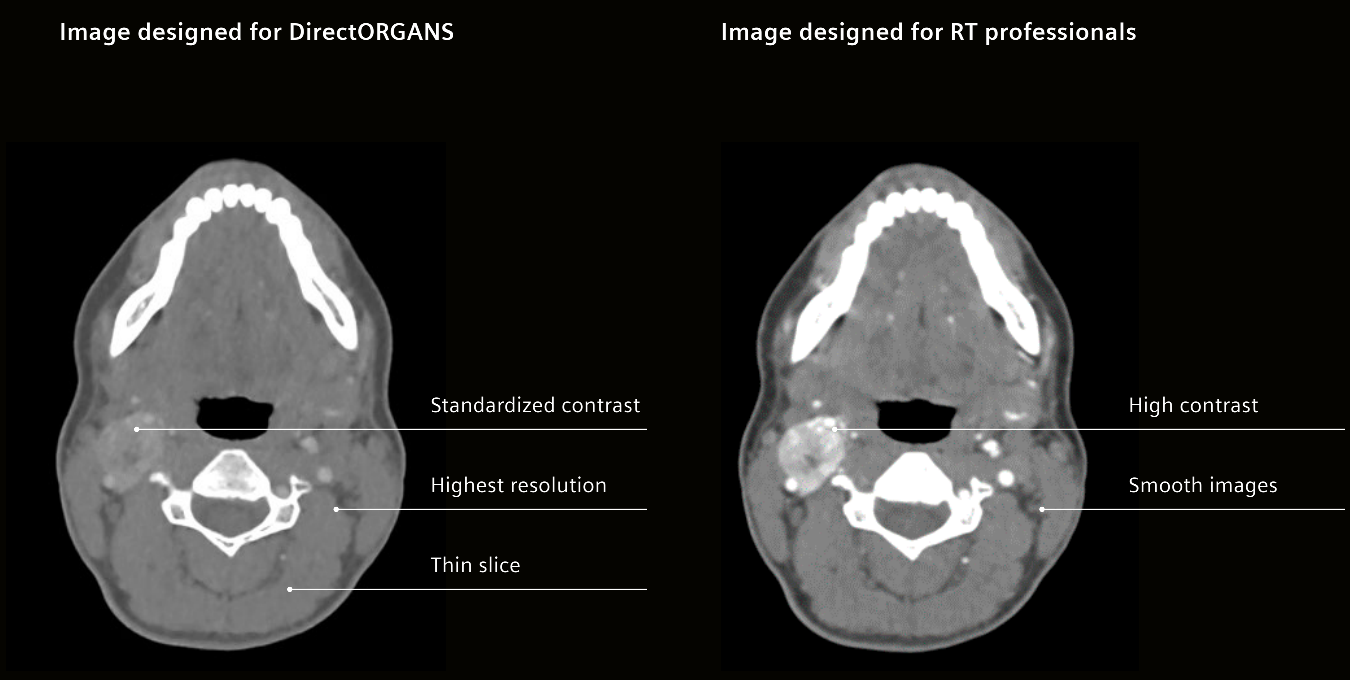


Fig. 2.1 Example of image designed for DirectORGANS (left) and RT professionals (right)

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].

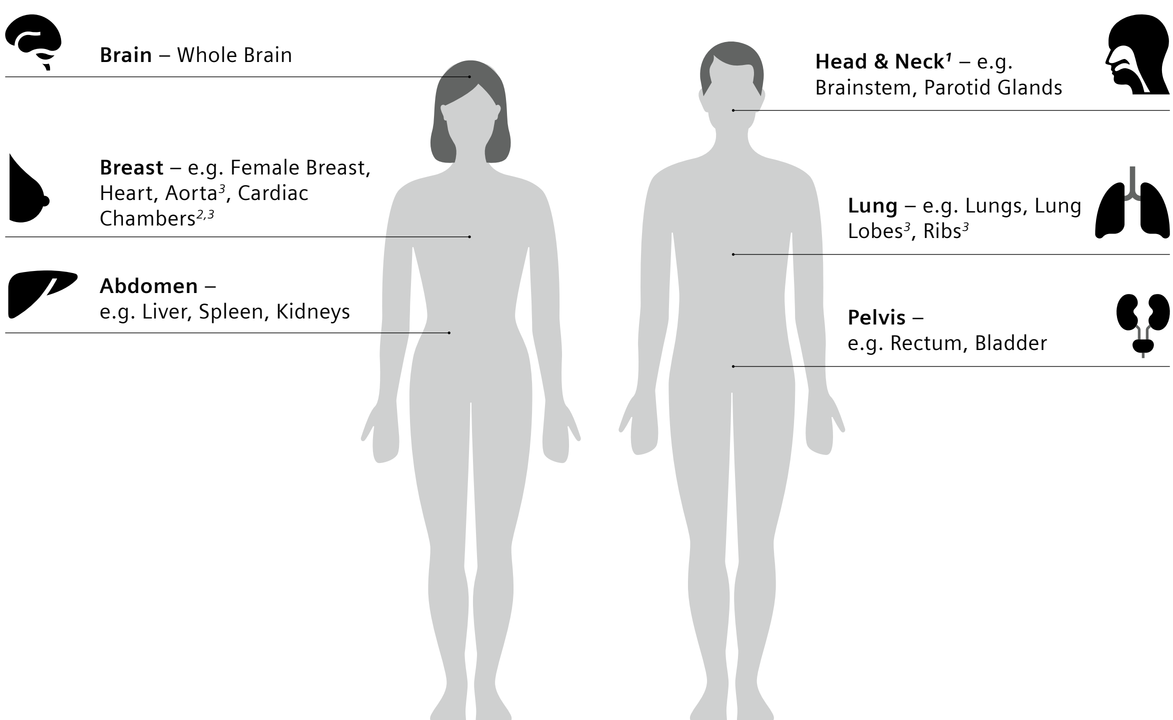


Fig. 2.2 Examples of contours generated by DirectORGANS and DirectORGANS Advanced (Software Version VA30)

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

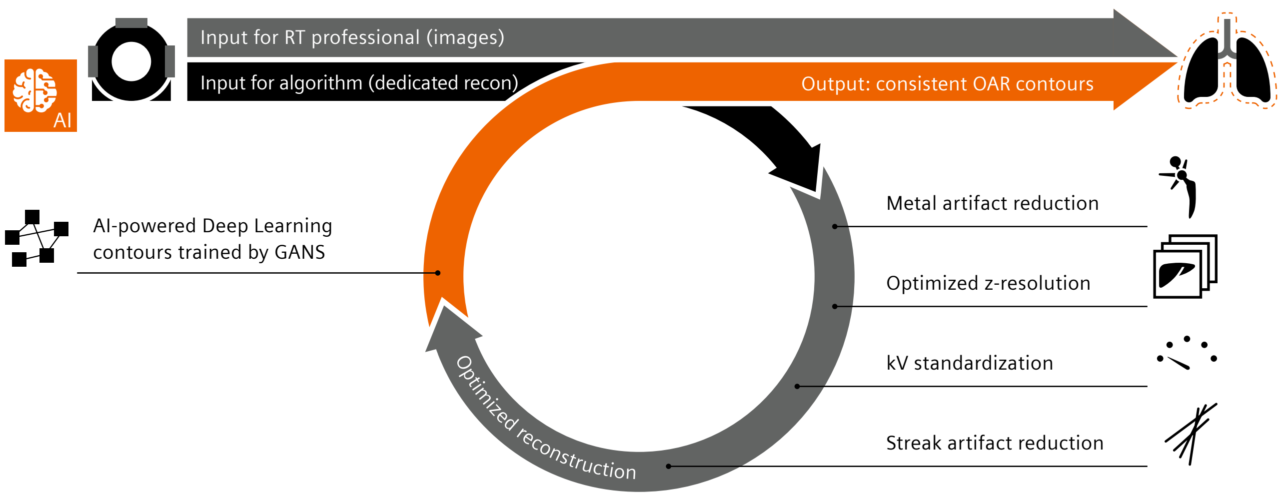


Fig. 2.3 Functional steps of the DirectORGANS algorithm

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.

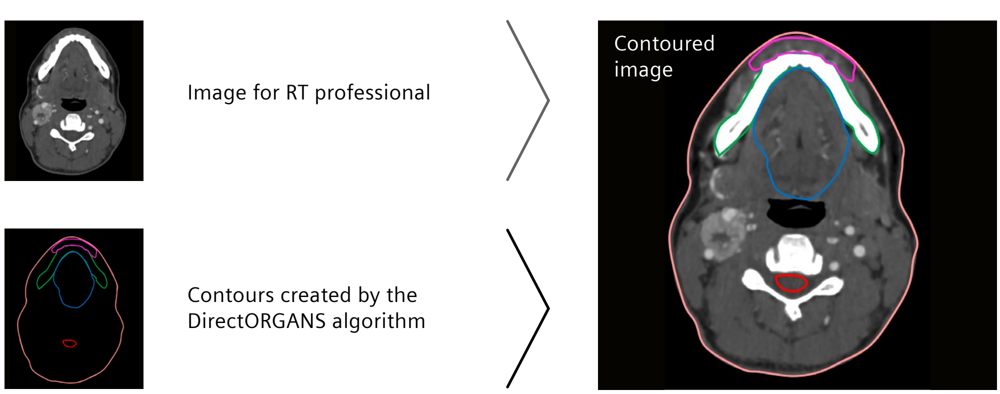


Fig. 2.4 The contours created by the DirectORGANS algorithm and the image optimized for human consumption are combined.
Courtesy of Radiology Department, Hospital Particular de Viana do Castelo, Viana do Castelo, Portugal

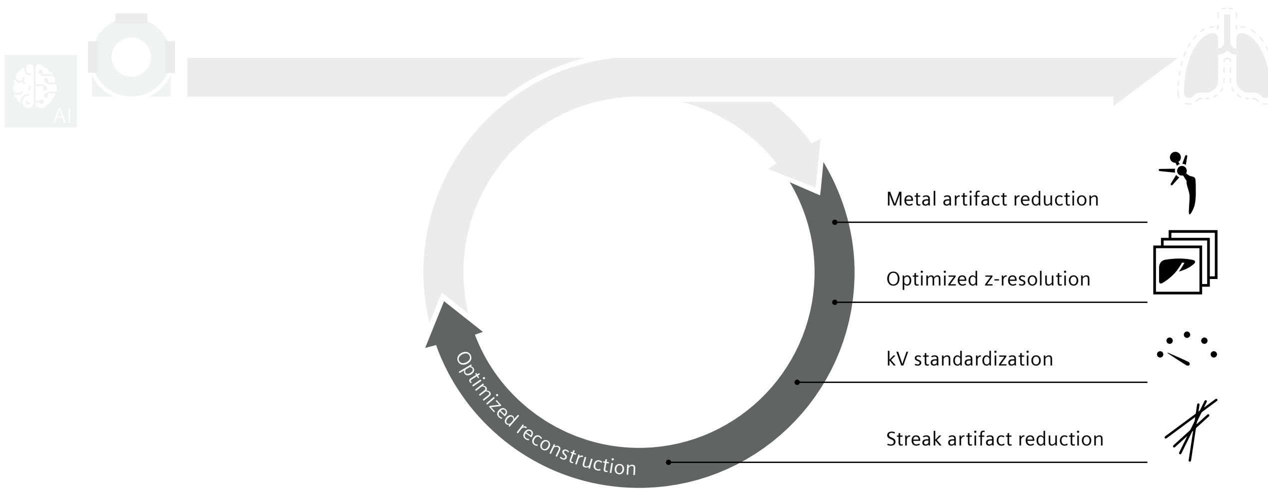


Fig. 2.5 Optimized reconstruction

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.

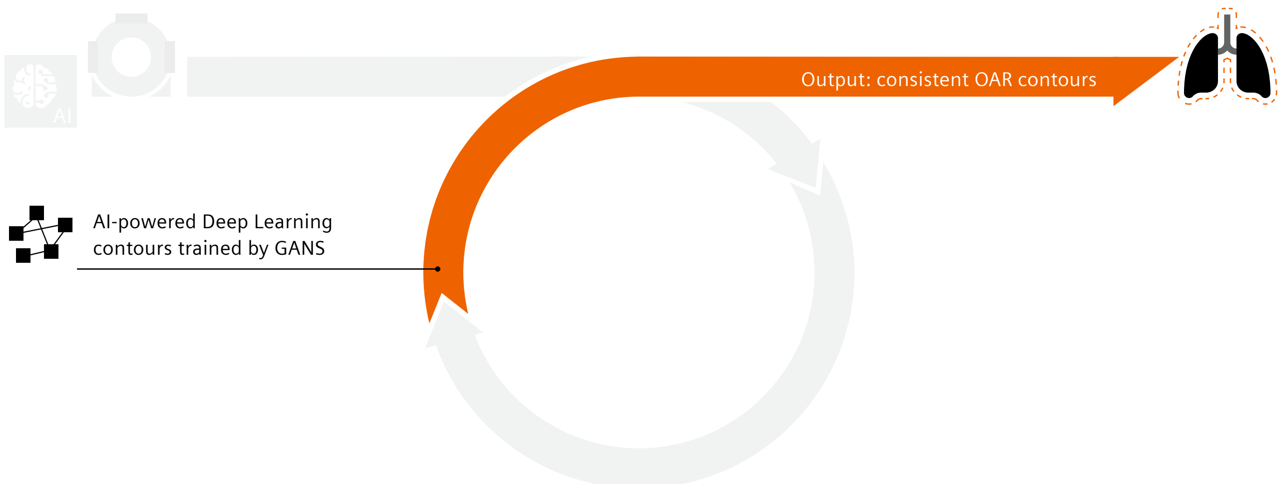


Fig. 2.6 Deep Learning Contouring

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].

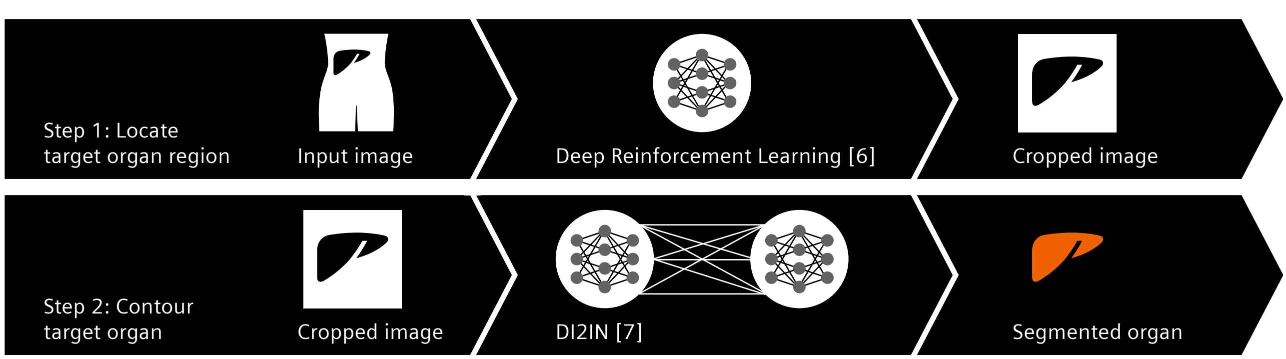


Fig. 2.7 Two step algorithm for DL based contouring

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

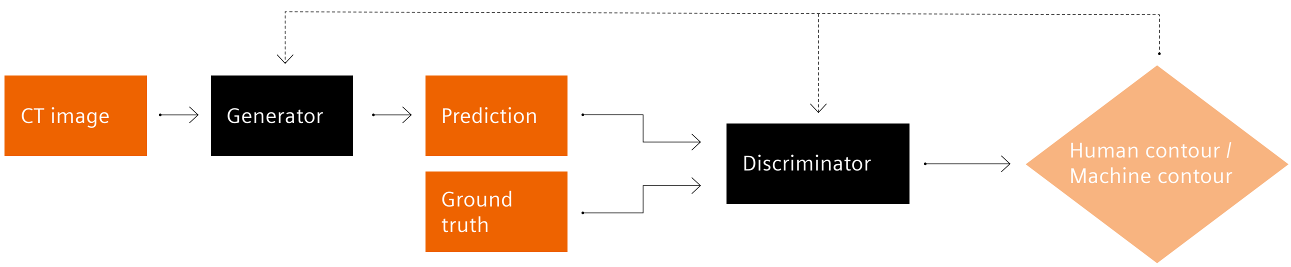


Fig.2.8 Adversarial training scheme

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 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.

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. By design, DirectORGANS enables a fully automated workflow requiring no additional workstation for the OAR contouring. This potentially leads to less errors originating from the application configuration or operation. As a result, time and resource saving can potentially be achieved as well as user independent results. With DirectORGANS OAR contouring becomes an integrated part of the standard CT acquisition.

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