

Generic User-guided Interaction Paradigm for Precise Post-slice-wise Processing of Tomographic Deep Learning Segmentations Utilizing Graph Cut and Graph Segmentation

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Abstract: State of the art deep learning (DL) manifested in image processing as an accurate segmentation method. Nevertheless, its black-box nature hardly allows user interference. In this paper, we present a generic Graph cut (GC) and Graph segmentation (GS) approach for user-guided interactive post-processing of segmentations resulting from DL. The GC fitness function incorporates both, the original image characteristics and DL segmentation results, combining them with weights optimized by evolution strategy optimization. To allow for accurate user-guided processing, the fore- and background seeds of the Graph cut are automatically selected from the DL segmentations, but implementing effective features for expert input for adaptions of position and topology. The seamless integration of DL with GC/GS leads to marginal trade-off in quality, namely Jaccard (JI) 1.3% for automated GC and JI 0.46% for GS only. Yet, in specific areas where a well-trained DL model may potentially fail, precise adaptions at a low demand for user-interaction become feasible and thus even outperforming the original DL results. The potential of GC/GS is shown running on ground-truth seeds thereby outperforming DL by 0.44% JI for the GC and even by 1.16% JI for the GS. Iterative slice-by-slice progression of the post-processed and improved results keeps the demand for user-interaction low.

1 INTRODUCTION

Precise segmentation with the need of no or only marginal user interaction is of high importance in computer-assisted medical diagnostics, both in research and clinical practice. Thereby automated and generally applicable image processing methods are still in focus of research. A fully automated albeit highly precise segmentation approach shipping as black box thereby is not necessarily of highest interest as the diagnostician always holds the ultimate responsibility for segmentation accuracy and diagnostic outcome. With the advances in medical image processing, a broad range of semi-automated

approaches is available for processing tomographic datasets, such as Region Growing, Live-Wire, Level Sets, Graph Cuts or Graph segmentation that are provided by various frameworks and tools (Strakos et al. 2015). While the radiographer or diagnostician using these tools and algorithms keeps full control of his actions, the achievable accuracy, the high demand for user interaction and the subjectivity of the findings and interpretations are a constant drawback during the last decades.

In recent years, the application of deep learning (DL) neural networks led to a sustainable impact in many segmentation domains in industry as well in medicine. Trained on a huge amount of reference datasets, these DL models allow for fully automated

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and highly precise segmentation, analysis and classification in specific diagnostic domains. Due to their black-box nature, the user must accept the generally impressive results as they are. Nevertheless, this is only acceptable as long as there is no need for adaptions. As no machine learning approach ever will have perfect sensitivity and specificity, the seamless integration of DL models in clinical routine necessitates for user-centric post-processing paradigms.

1.1 State of the Art and Related Work

In the domain of fully automated segmentation, classic approaches such as Statistical Shape Models (Cootes et al. 1992) utilizing PCA or Active Appearance Models (Cootes et al. 1998) need to be adapted for specific domains, modeling the shape variability and finding individual concepts for robust positioning, registration and reference point determination.

In recent years, the advance in GPU hardware and machine learning frameworks enable deep neural networks to find their way into industrial and medical image processing and computer vision domains. While feed forward neural networks are successfully applied for multi-modal image fusion (Zhang and Wang 2011), self-organizing neural networks allow clustering in complex domains such as classification of renal diseases (Van Biesen et al. 1998). Deep semantic knowledge as present in natural language processing is covered by incorporation of recurrent cycles introduced by Hochreiter (Hochreiter and Schmidhuber 1997) as long short-term memory (LSTM) showing huge potential for predicting diagnostics from several input sources (Lipton et al. 2015). First deep feature networks were introduced with Haar Cascades (Viola and Jones 2011), thereby combining and boosting a large number of weak convolution features at varying scale. A specific CNN architecture perfectly applicable for medical image segmentation in 2D and 3D is the U-Net architecture (Ronneberg et al. 2015) (Cicek et al. 2016).

In the field of user-centric segmentation approaches, conventional Region Growing, LiveWire Segmentation (Mortensen and Barrett 1995) and Graph cut (GC) (Boykov et al. 1998) are of high relevance utilizing input image intensities or edges. Graph cut refers to application of min-cut/max-flow algorithms from the domain of combinatorial optimization, generally utilizing Gaussian mixture models (GMM) as fitness function. Graph cut is perfectly applicable to user-guided video processing at low demand for interaction and high accuracy. With the GMM iteratively improved along the border

areas, denoted as Grab cut (Rother et al. 2004), the results achievable by conventional Graph cuts are further improved.

Combination of high-quality DL segmentation with applications for user-guided post-processing is a topic of ongoing research. In the work of (Sakinis et al. 2019), the DL model is trained together with reference user markers roughly indicating the target shape. Thus, after training, these markers are placed and adapted to control the contour in incorrect areas in an iterative optimization process. Thereby, the DL model has learned to obey the user markers. While this is a very intuitive and adequate solution, the application to arbitrary DL models is not possible as the image data always has to be trained together with reference user adaptions. A similar approach for real-world RGB images is presented in the work of Xu et al. (Xu et al. 2016), where Euclidean distance maps calculated from user-clicks are provided as channel for a fully convolutional network (FCN) and graph cut is used to refine the probability segmentation resulting from the FCN.

In the domain of GC, Boykov demonstrated the benefit of arbitrary fitness functions, thus modelling an energy function similar to snakes or geodesic contours where edges are incorporated too (Boykov and Funka-Lea 2006).

1.2 Graph Cut / Segmentation for User-guided Post-processing of DL

To overcome the limitations of DL segmentation models with respect to frequently needed post-processing, the utilization of Graph cut and Graph segmentation technology is evaluated in this paper. We present a generic approach that is perfectly applicable for post-processing all kinds of segmentations. Instead of a GMM, the graph weights are derived from the DL segmentation combined with edge information from the original slice. To allow for inevitable user intervention only, the foreground (FG) and background (BG) seeds for the graph are derived from the DL segmentation, too. Thus, user-interaction after visual inspection is in the range between simple confirmation of the initial segmentation result and mild adaptions by altering the FG and BG graph.

2 MATERIAL

For training, validation and testing 131 abdominal CT datasets of the liver from the Medical Segmentation Decathlon database (MedDecathlon 2019) providing

reference segmentations are used. After scaling to iso voxel spacing, 27,000 slices are split into a training set (22,500) and a validation set (4,500) with strict separation of the volumes. All slices are clipped to size 308x372 with a 10 pixel outer margin around the borders for reasons of data augmentation during DL model training.

The input slice intensities a_i are rescaled to 8bit in range 0 to 255 with mean intensity value μ_{liver} per volume shifted to 127.0, transformed according to scale factor s and truncated to [0;255], see Eqn. 1-2.

$$s = \frac{115}{3 \cdot \sigma_{liver}} \quad (1)$$

$$T(a_i) = \begin{cases} 127 - |a_i - \mu_{liver}| \cdot s & a_i \leq \mu_{liver} \\ 127 + |a_i - \mu_{liver}| \cdot s & a_i > \mu_{liver} \end{cases} \quad (2)$$

For DL segmentation, a U-net cascade approach is utilized, thereby incorporating axial, sagittal and coronal views for improved robustness (Zwettler et al. 2020), see Fig.1. The reconstructed axial segmentations from S_{axial} , S_{sagittal} and S_{coronal} input are thereby slightly varying and combined with another U-net expecting these three input channels per slice leading to robust segmentation S_{comb} . These DL segmentations utilized as testing data for this research work are of good quality with DSC=97.5 and JI=95.2 for S_{comb} . The single slice results are e.g. DSC=96.2 and JI=92.6 for S_{axial} . In the work of Zwettler et al. (Zwettler et al. 2020) another improvement incorporating spatio-temporal aspects between neighbouring slices was presented increasing to DSC=98.9 and JI=97.9 overall. This improvement is not applied for this paper to allow the evaluation of the GC and GS potential for correcting DL models in an unbiased and objective manner.

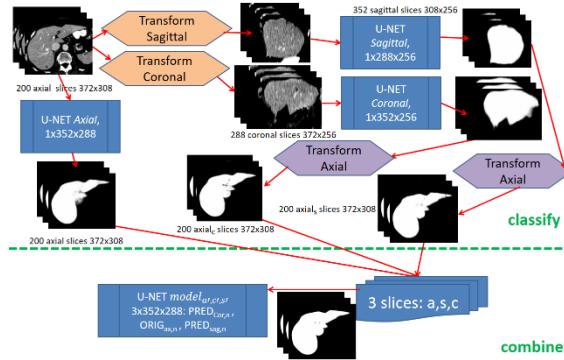


Figure 1: The slice-wise segmentations are performed in axial, sagittal and coronal view utilizing specific U-nets. Another U-net then combines the three slices as input for processing the final segmentation result.

To perform a GC study, two test sets with each $n=30$ slices randomly selected from the validation set

are utilized. The test sets refer thereby to intervention with and without skeleton support. Within the 30 slices, the initial segmentation comes from the axial view only (10), from combined U-net model (10) and axial with manually applied errors (10), i.e. left out parts, closed/opened vessels or attached artefacts. A group of three test persons, all experts in medical image segmentation, evaluates these 60 slices.

To test the result propagation in case of user post-processed DL results with Graph cut/segmentation, the $m=10$ volumes from the Medical Segmentation Decathlon database are manipulated within the 3D volume in areas of topographic changes of the liver parenchyma in axial view. This way, the propagation of corrected results is evaluated on the slice stack.

3 METHODOLOGY

To allow for seamless post-processing of DL segmentation results utilizing GC or GS, a specific fitness function is required as input. Thereby, the

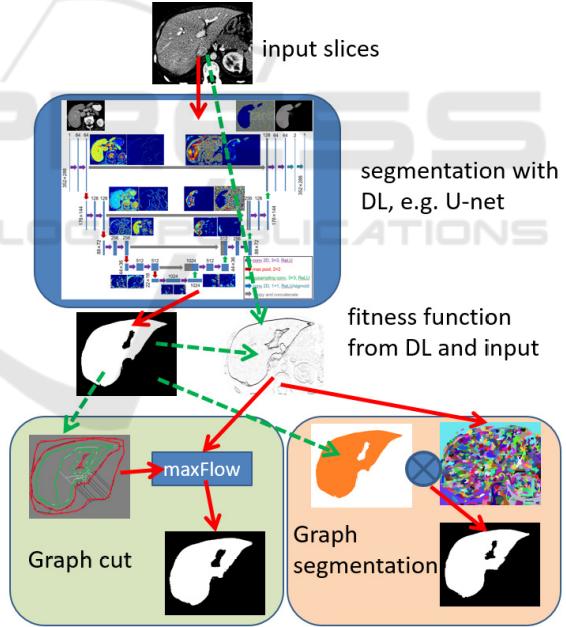


Figure 2: Process Overview. Based on DL segmentation results and original image (gradients), a fitness function is calculated. Graph cut is then performed with FG and BG seeds (red and green) from the DL segmentation and the fitness function utilizing *maxFlow*. For Graph segmentation, the fitness function is used for pre-fragmentation. The pre-fragmented regions are selected according to at least 0.5 overlap-ratio compared with the DL segmentation. Both GC and GS allow for expert user adaption by either altering the FG and BG seeds or selecting/unselecting the GS regions.

fitness function incorporates the DL results as seeds to conserve the high accuracy at the provided flexibility of expert user-centered post-processing. The process overview is shown in Fig. 2 while the utilized fitness functions are illustrated in Fig. 3.

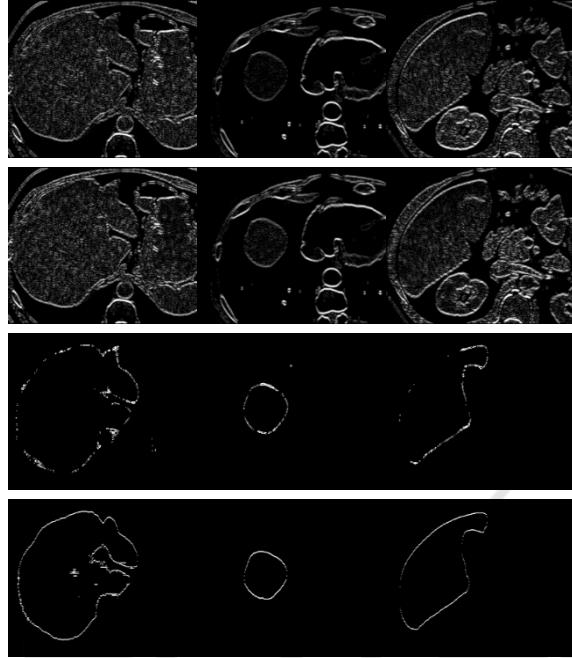


Figure 3: Per column illustration of horizontal results ORIG, EXP, S1 and S4 for the datasets #506, #13789 and #11623 as basis for fitness-function.

For each slice i , the original image $ORIG_i$, the expected intensity profile EXP_i , and the segmentations Sax_i , $Ssag_i$, $Scor_i$ and $Scomb_i$ (axial, sagittal, coronal and combined) are incorporated in the fitness function:

ORIG: horizontal (H) and vertical (V) edges of the original intensity profile after shift to $\mu_{int} = 127$ window centre as $ORIG_{Hi}$ and $ORIG_{Vi}$ respectively, cf. Eqn. 1.

EXP_i: H and V edges of the original image damped or amplified by a difference image from the expected intensity level processed by a median filter $r = 1$ followed by Gaussian smoothing ($r = 5$, $\sigma = 2.5$), referred to as EXP_{Hi} and EXP_{Vi} respectively.

S1_i and S4_i: H and V edges from the binary segmentation results from axial, sagittal, coronal and combined with 1 and 4 hits per voxel respectively as $S1_{Hi}$, $S1_{Vi}$, $S4_{Hi}$ and $S4_{Vi}$. The 2 and 3 hit cases are omitted due to expected high correlation and thus low entropy. Thus, either a pixel is an element of all segmentations or only of one to handle the optional segmentation regions $S1_i$.

Conservation of the gradient magnitude is of high relevance for calculating the cumulated fitness function. Thus, for the combination of $ORIG_i$, EXP_i , $S1_i$ and $S4_i$, a max-operation is preferred over building the mean. To combine the four edge images utilizing a max function

$$F_i = \max \left(\frac{s(ORIG_i, w_0)}{s(S1_i, w_2)}, \frac{s(EXP_i, w_1)}{s(S4_i, w_3)} \right) \quad (3)$$

with function $s()$ for scaling to $[0; w_i]$, an adequate set of weights w_j is required, thereby conserving the segmentation outcome of the DL model and still allowing adaption with respect to original image intensities. These weights need to be calculated for each segmentation domain, e.g. liver parenchyma from CT modality, only once. The weights are thereby optimized utilizing Evolution Strategy (ES) with recombination $(\mu/\rho+, \lambda)$ with $epochs=100$, $batchSize=8$, $populationSize=8$, children $\lambda=32$, $mutationChance=0.4$, $mutationRate=0.25$ dropping by around 4% each epoch. The fitness function is calculated for vertical and horizontal orientation as F_{Hi} and F_{Vi} , respectively.

The fitness landscape is considered very flat and ambiguous as only the proportion of the weights is of relevance. As max-flow execution takes 400ms per slice, a higher number of epochs or larger batch sizes are not practical. Instead, iterative refinement using the ES is applicable.

3.1 Graph Cut Method

To facilitate little need for user interaction, the FG and BG markers for Graph cut are derived from the DL segmentation mask $Scomb_i$ for slice i as initialization. The FG and BG markers thereby comprise a skeleton with minimal distance $minDist=5$ from the FG/BG borders together with inner region boundaries at a distance of $borderDist=10$, see Fig. 4. A topological cut of the skeleton graph when demanding $minDist=5$ is omitted which is of high relevance in narrow sections, i.e. the minimum distance is only enforced for leaf-sections of the skeleton graph.

In case of inaccuracies, the user alters the FG and BG markers suggested by the algorithm, i.e. by removing/adding seeds for both, the BG and the FG. With the FG and BG seed markers provided, the Graph cut is performed on fitness image F_i leading to graph-cut post-processed image GC_i .

3.2 Graph Segmentation Method

Based on the same fitness function F_i as used for the Graph cut, a graph segmentation algorithm is applicable leading to a watershed-like fragmentation of the input image denoted as GS_i with fragmented regions $R_j \subseteq F_i$. To transfer GS_i with j region labels back to a binary segmentation representation, each region R_j is either assigned a FG or BG label, according to the largest intersection set with DL result $S_{comb,i}$ leading to result segmentation GS'_i , see Equation 4 with pixel $(x, y) \in R_j$.

$$GC'[x, y] = \begin{cases} FG & |R_j \cap S_{comb}[FG]| \geq |R_j \cap S_{comb}[BG]| \\ BG & \text{else} \end{cases} \quad (4)$$

Thus, the binary label assigned to the pixel coordinates of each region R_j result from majority voting of pixel-wise AND operation with the DL segmentation $S_{comb,i}$, see Fig. 5.

Besides running this process in a fully automated way, i.e. utilizing the DL outcome for selecting the FG regions from Graph segmentation, the user can correct results too by selecting/unselecting the fragmented regions.

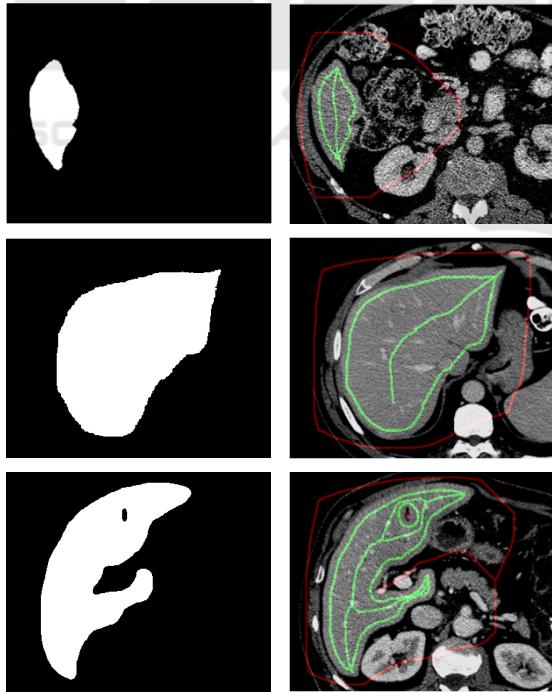


Figure 4: From the deep learning result $S_{comb,i}$ (left column), the FG markers (green) are derived as skeleton besides the inner contour with distance $borderDist=10$ to the binary contour borders. The outside marker (red) is calculated as skeleton from background in $S_{comb,i}$.

3.3 Slice-wise Propagation of Post-processed Results

In case of slice-wise processing a tomographic volume in axial direction, due to the high resolution of the imaging modalities the pixel-wise differences of two neighbouring slices $slice_i$ and $slice_{i+1}$ is expected to be marginal. Furthermore, the automatically derived FG and BG markers for Graph cut show a safety margin to the border areas. Thus, the manually corrected results after user-guided Graph cut post-processing of slice $slice_i$ denoted as GC_i can be applied as basis for FG and BG markers of the subsequent slice $slice_{i+1}$. Consequently, FG and BG markers are derived from GC_i instead of $S_{comb,i+1}$ for slice $slice_{i+1}$.

The same slice-wise propagation of corrected results is applicable for the Graph segmentation approach elucidated in section 3.2, too. Thereby, the corrected / post-processed GS'_i replaces $S_{comb,i+1}$ for slice $slice_{i+1}$ by combining with $GS'_{i+1} = GS'_i \cap GS_{i+1}$ instead. The fragmented regions after Graph segmentation yield sharp edges in the border sections and thus expected to be tolerant by applying the corrected previous slice for logic combination.

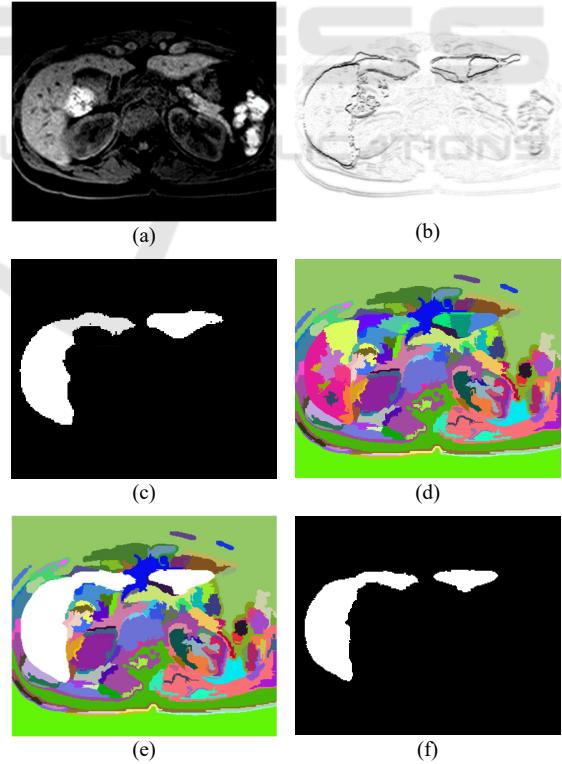


Figure 5: Based on input slice i (a) the fitness function F_i (b) is used for Graph segmentation GS_i (d). With DL segmentation result $S_{comb,i}$ (c) the regions are combined as $S_{comb,i} \cap GS_i$ (e) leading to binary result GS'_i (f).

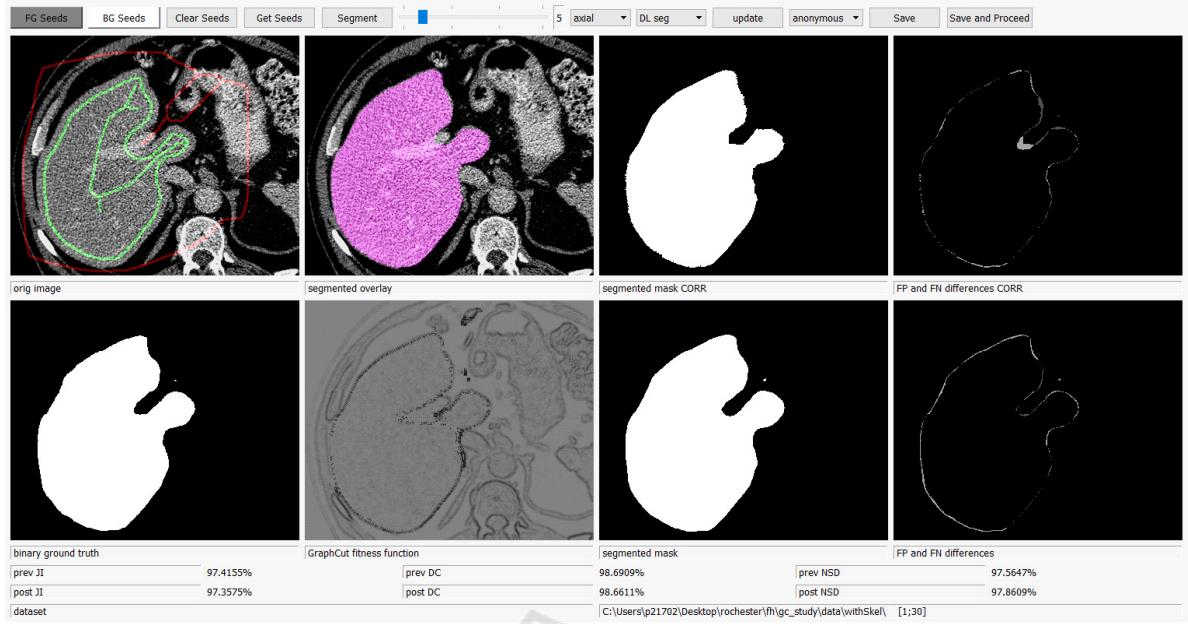


Figure 6: GC GUI in non-study mode showing full information. After adaptions by the user, the JI is increased from 0.974 to 0.977 compared to the axial DL model.

4 IMPLEMENTATION

A prototype for GC post-processing is implemented with Python using *PyQt5* for the GUI and library *maxflow* for the GC implementation as proposed in (Zabriskie 2020) for RGB images.

Besides the input slice, the GC fitness, the GC result and a FP/FN view of the adapted result, also the results from the DL model together with a FP/FN view of the initial results as well as the ground truth are presented. Furthermore, the quality metrics JI, DC and NSD are evaluated, see Fig. 6.

For the study, only input slice and GC results are presented and no quality metrics reported to do not give the test persons a hint for the correct and expected outcome regarding the ground truth.

5 RESULTS

Evolution Strategy optimizes the weights for ORIG (w_0), EXP (w_1), S1 (w_2) and S4 (w_3) with $w_0=0.287$, $w_1=0.217$, $w_2=0.419$, $w_3=0.641$, cf. Fig. 7.

The result slices with maximum-function applied and scaled to the target weights are shown in Fig. 8. Thereby, the fitness function combines an edge representation of the binary segmentation as well as input image information.

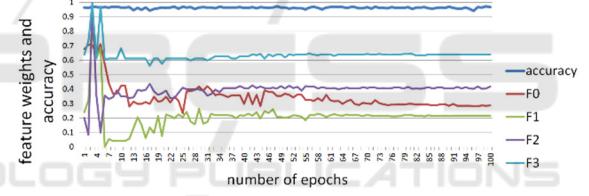


Figure 7: Parameter optimization of weights w_0-w_3 for the first 100 epochs with achievable accuracy close to 1.0. Despite the absolute weights, only the relative proportion is of relevance with stability in rank after around 60 epochs.



Figure 8: Horizontal edges of the combined fitness function for slices #506, #13789 and #11623 respectively.

5.1 Graph Cut Post-processing

5.1.1 Automated GC Test Runs

With the FG and BG derived from the initial DL segmentation, cf. Fig. 9, almost the same accuracy is reached in a fully automated way, see Tab. 1 processing all $n=4859$ slices. Due to the Graph cut processing, the JI marginally drops by 1.3% on

average ($+537=55-4267$) yet allowing the user to correct obviously incorrect areas on demand. If the FG and BG marker skeletons are derived from ground truth reference segmentations, the DL accuracy is even outperformed by the GC based post-processing by 0.44% JI and improving 2846 of the slices ($+2846=1-2012$), indicating the GC potential in post-processing.

Table 1: Achievable *Jaccard (JI)*, *Dice Coefficient (DC)* and *Normalized Surface Distance (NSD)* tested on $n=4859$ slices for original DL models, GC with skeleton from DL and GC with skeleton seeds from the ground truth (GT). Thereby, GC is applied in a fully automated way.

metric	DL	GC, DL seeds	GC, GT seeds
JI	.9488	.9358	.9532
DC	.9737	.9668	.9760
NSD	.9507	.9488	.9602

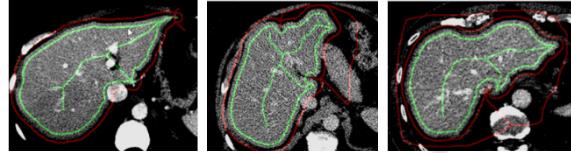


Figure 9: The FG (green) and BG (red) skeletons and inner surface borders are well suited for performing GC segmentation almost at the same accuracy as the input DL model results.

5.1.2 Manual Post-processing

With support of the skeleton for the three test persons, processing of the 30 slices took on average 35.3sec per slice and 51.3sec for the 30 slices of the dataset without skeleton support. With the preset skeleton to adapt, the average amount of FG and BG seeds per slice is 1915.8 achieving an average accuracy of JI=.9573 and DC=.9782 and NSD=.9589 compared to the axial DL model with JI=.9548, DC=.9769 and NSD=.9577 at 1772.6 seeds per slice on average, see Fig. 10.a. Thus, due to manual post-processing, the average accuracy is increased. On average 16 out of 30 slices outperform the DL model, mainly the ones with small applied errors. For slices with already a high quality result from the DL model, results rather get worse as expected due to GC discretization.

Without skeleton support, the test persons place 1099.7 seed pixels on average achieving an accuracy of JI=.9265, DC=.9618 and NSD=.9206 compared to JI=.9251, DC=.9611 and NSD=.9192 at 1873.6 seeds per slice on average, see Fig. 10.b. Generally, results are quite invariant w.r.t. placed FG and BG markers.

Thus, results are very robust and “drawing” close to the borders is not necessitated, see Fig. 11.

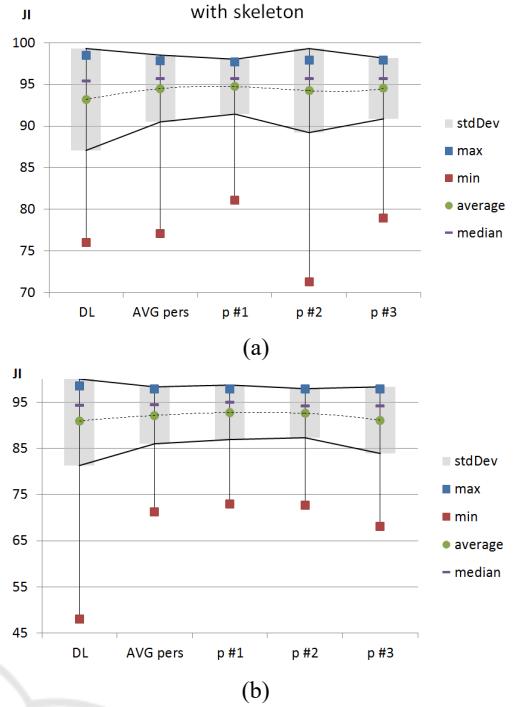


Figure 10: JI for GC results with (a) and without skeleton support (b). The accuracy of the DL model is conserved, while the standard deviation and min/max range is generally reduced.

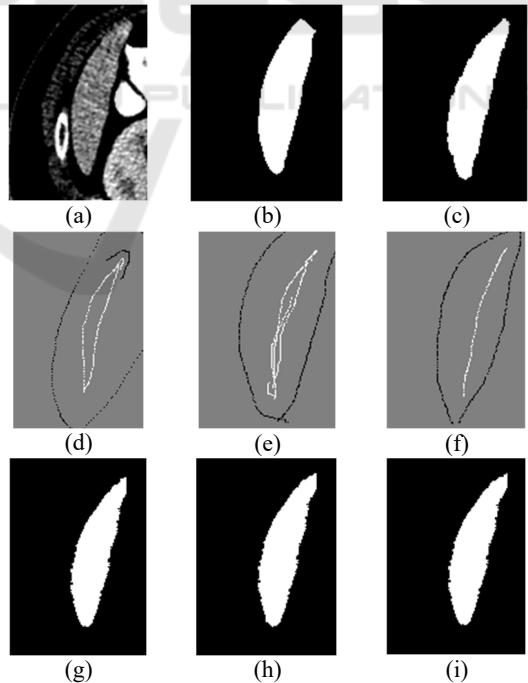


Figure 11: Slice 28 (a) without skeleton support and expected ground truth (c) with suboptimal DL result JI=.877 (b) can be improved by all test persons (g-i) in range [.911; .920]. The axial error of missing upper part can be corrected with different skeleton interpretations (d-f).

With GC post-processing the obvious errors are corrected as indicated by the smaller JI standard deviation calculated for the slices with $\sigma_{JI,users}=.0400$ compared to $\sigma_{JI,DL}=.0614$ for the DL model all with skeleton support. Without the skeleton support, similar results are noted, namely $\sigma_{JI,users}=.0613$ compared to $\sigma_{JI,DL}=.0964$.

5.2 Graph Segmentation Post-processing

Running Graph segmentation on DL results of the MedDecathlon test datasets in an automated way, the trade-off between the deep learning results and the Graph segmentation results is low. While for DL, accuracy of $JI=94.88\%$ is reported, the Graph segmentation leads to $JI=94.42\%$, which is a marginal drop by 0.46%, see Table 2.

Table 2: Achievable Jaccard (JI), Dice Coefficient (DC) and Normalized Surface Distance (NSD) tested on $n=4857$ slices for original DL models, GS with auto-selection from DL and GS with selection from the ground truth (GT).

metric	DL	GS auto-run	GS, using GT
JI	.9488	.9442	.9604
DC	.9737	.9713	.9798
NSD	.9507	.9478	.9702

If the ground truth (GT) is used for assigning the fragmented regions the BG and FG label respectively, then the accuracy can theoretically be gained to $JI=0.9604$ showing high potential in post-processing.

The $n=4,857$ test slices are thereby fragmented into 2,829,228 regions utilizing a minimum region size $reg_{min} = 40$ and a constant border threshold $K = 50$. Most of these regions are perfectly overlapping with the DL pre-segmentation, namely 27.86% for the FG and 64.84% for the BG. These perfect matches are thus classified at very high confidence. Only the remaining regions close to the border areas that are partly overlapping with both, BG and FG areas of the DL segmentation, need to be assigned according to majority voting. From these regions, 1.96% are probably FG, i.e. FG ratio ≥ 0.5 and 5.33% probably BG, i.e. BG ratio < 0.5 . Nevertheless, even these regions show a clear trend for either FG or BG, which becomes obvious from the average DL classification values per region. For the probably FG regions, this average $\mu_{probFG} = 230.18$ is far above the equilibrium at 127.5. Similarly, for the probably BG regions, $\mu_{probBG} = 28.52$ indicates high confidence. Thus, even for the small amount of

regions fluctuating between FG and BG, they show a clear trend for either BG or FG.

5.3 Slice-wise Propagation of Post-processed Results

To test the propagation of both, GC and GS post-processing, four datasets are prepared, namely:

- case 0: slices 22504-22516 with correct axial
- case 1: slices 22504-22516, all views invalid
- case 2: slices 25004-25012 with correct axial
- case 3: slices 25004-25012, all views invalid

For these test cases, the sagittal, coronal and combined DL results are manipulated in the selected slice range, cutting a part of the liver parenchyma, see Fig. 12. By adding test cases with and without invalid axial input the 1 or 4 hit count of the fitness function is tested.

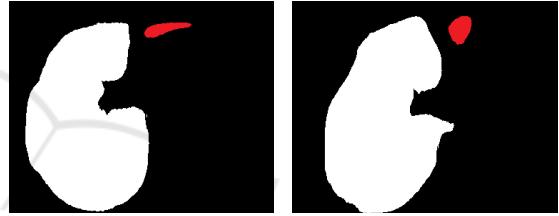


Figure 12: For the test cases 0/1 (left, combined slice #22505) and 2/3 (right, combined slice #25005) the caudal part of a liver lobe is removed from the DL results, shown as red areas in the images.

As shown in Table 3 and Table 4, for all test datasets the automated propagation of the corrected first slice leads to an improvement of the subsequent slices too. Thus, the missing part in the DL segmentation, i.e. parts removed for testing purposes, are precisely reconstructed, see Fig. 13 for slice #2512.

Table 3: Slice-wise propagation of the corrected first slice for test cases 0 and 1 in slice-range 22504-22516.

metric	DLerr	case 0		case 1	
		GC	GS	GC	GS
JI	0.9176	0.9403	0.9584	0.9385	0.9534
DC	0.9570	0.9692	0.9788	0.9683	0.9762
NSD	0.9019	0.9424	0.9632	0.9405	0.9575

Table 4: Slice-wise propagation of the corrected first slice for test cases 2 and 3 in slice-range 25004-25012.

metric	DLerr	case 2		case 3	
		GC	GS	GC	GS
JI	0.9073	0.9246	0.9321	0.9216	0.9262
DC	0.9514	0.9608	0.9648	0.9592	0.9617
NSD	0.8850	0.9306	0.9292	0.9275	0.9190



Figure 13: Results prior and post propagating the corrections from slice to slice. By adding the missing part thanks to FG/BG marker from previous slice, the JI is increased from $JI_{prev}=0.8624$ to $JI_{post}=0.8971$.

Comparing test case 0 to 1 and test case 2 to 3 it becomes obvious, that results drop a bit. Consequently, the fitness function decreases in quality, if not even the axial direction is correct and all segmentation is solely performed on input image edges, see Fig. 14.



Figure 14: With correct DL results (left), the fitness function shows sharp edges in the test area, while for one axial hit (middle) and zero hits (right) the missing liver part is vanishing, marked with red arrows.

The slice-wise automated propagation of user corrected slices is applicable for GS strategy too as compared in Tables 3-4, thereby even outperforming the Graph cut approach. For case 0 the $JI_{prev}=0.9176$ is increased to $JI_{postGS}=0.9584$ while $JI_{postGC}=0.9403$ is around 1.8% below.

Analysing the FG/BG ratio it becomes obvious, that most regions still show 100% congruency with either FG or BG and for the in-between regions, $\mu_{probFG} = 230.75$ and $\mu_{probBG} = 24.24$ respectively indicate, that at high resolution of the tomographic volume in z-direction, the corrected results of the previous slice can be applied in a very robust way. With GS propagation, the one and zero hit cases (0/2 and 1/3) perform at very comparable accuracy, see Fig. 15 for slice #25012 in test case 1 with the object borders strong enough for GS fragmentation even in case the DL models lack correct results.

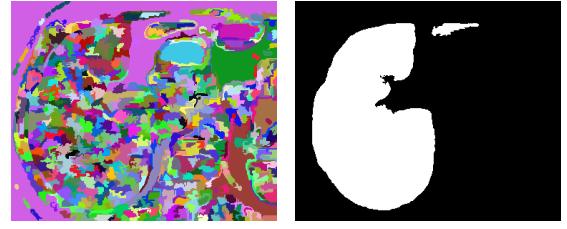


Figure 15: For the test case with zero hit count, shows still borders strong enough to facilitate result-propagation with GS for significantly improved accuracy.

6 DISCUSSION

Preparing results of binary segmentation together with edge information of the original slices allows the utilization of GC or GS as generic tool for user-guided post-processing. In case of significant misclassification, results from DL models or other segmentation strategies can be corrected in a post-processing step by experienced analysts. Thus, one can benefit from the high classification accuracy of well-trained DL models and yet overrule the black box outcome in case of obvious discrepancies.

The trade-off in quality of the GC method with seeds derived from the DL results is marginal due to fitness function weights optimized by ES. Utilizing the same fitness function, the trade-off for GS is to be considered even lower.

Propagation of corrected slices as pattern mask to the subsequent slices for automated post-processing allows for significant reduction in user interaction, yet featuring high quality result. Thereby, GS outperforms GC w.r.t. both, accuracy and robustness. This is the fundament for innovation in user-guided image processing, thereby incorporating the accuracy and precision of well-trained DL models together with adequate interaction paradigms for user-guided post-processing in rare cases of error.

Although the trade-off in accuracy of GC post-processing is marginal compared to particular DL models, there is still potential for further improvement. Instead of constructing the pixel graph with N_4 adjacency based on vertical and horizontal edges derived from the fitness function, one can extend to N_8 additionally incorporating diagonal edges to overcome the GC tendency of straight edges and discrepancies in narrow region areas. The same improvement is applicable to GS strategy.

With respect to the user interaction, instead of mouse-based FG and BG pixel-area masking for GC, the skeleton graph could be manipulated too, i.e. sub-

tree parts removed by selection, thus further improving efficiency.

7 CONCLUSION AND OUTLOOK

In diagnostic domains with initial lack of training data, DL models cannot be trained at highest accuracy from the very beginning. Yet, both the GC and the GS post-processing allow to post-process routine datasets and thus allow for steady improvement and adaption of the DL models if iteratively trained on the enlarged reference data. The chicken-egg problem of an insufficient amount of training data in the DL domain tackling new diagnostic domains is conquered by applying the proposed strategy.

Future test runs will focus on different imaging modalities and anatomies as well as on low-data DL training tasks with incrementally enriching the database with GC or GS post-processed reference segmentations.

To conclude, the proposed method shows a very high potential for application in medical diagnostics, meeting the needs of a real hospital environment, i.e. large number of patients and highly accurate segmentation. The generic approach does not require adaptions on the network architecture or training process and thus is applicable to both, arbitrary deep learning models and arbitrary diagnostic domains.

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