An multi-shape loss function with adaptive class balancing for the segmentation of lung structures

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Segmentation of small anatomical structures (like airways and pulmonary vessels) is a highly unbalanced problem that poses a main challenge for accurate performance of deep learning methods. Unlike classification problems, segmentation balancing cannot always be approached using a suitable selection of the training samples. An alternative to sample selection is to formulate a loss function mitigating class imbalance [1]. Current approaches relay on a weighted multiclass loss with weights computed according to the frequency of each class in the training set. Losses with constant weights computed from the whole training population might be inappropriate in case of processing 3D volumes by either patches or slices, since it is not guaranteed that they contain all classes in the same proportion as they are in the whole population.

In this work, we propose a weighted average of each class loss with weights computed for each sample in the training set in a multi-organ approach. To further alleviate class imbalance, organs are grouped into classes according to their geometrical type: spherical, tubular, cylindrical or unstructured. Geometrical classes are split into organs according to their appearance and texture using convolution with a bank of filters in a post-filtering step. Our approach has been tested in a UNet architecture for the segmentation of lung structures in CT scans.

The loss function we propose to tackle with multi-organ unbalanced segmentations is a weighted average of the DICE score computed for each organ with weights adapted to each sample in the training set. The DICE score is a gold-standard measure of volume overlap between a binary segmentation mask, namely Seg, and a ground truth mask, namely GT, given by:

$$DSC(Seg,GT)=2|Seg\cap GT|/(|\mathrm{Seg}|+|GT|)$$

In a multi-organ segmentation problem with c=1,…,N organs to be segmented, let Seg_{i^c}, GT_{i^c} be, respectively, the segmentation and ground truth masks of organ *c* for the *i-th* sample in the training set. Then, we define its weighted multi-organ DICE score as:

$$DSC_i:=DSC(Seg_i,\ GT_i)=1-\sum^{N}_{c=1} w^i_c\ DSC(Seg_{i^c}\ ,\ GT_{i^c})$$

$$w^i_c=\rho^i_c\ /(\sum^{N}_{c=1}\rho^i_c);\ \rho^i_c=P^i_t/P^i_c$$

being P^i_t is the total number of pixels/voxels (of all the classes) in the i-th training sample and P^i_c is the number of pixels/voxels in the i-th sample that belong to the class *c*. The loss function that we propose is formulated as:

$$Loss:=1/N_{Samp}\sum_i DSC_i$$

In order to further mitigate imbalance, instead of considering each organ as a class, they are grouped into according to the topological type of its anatomical shape into 4 classes: spherical, cylindrical, tubular and unstructured. Organs belonging to the same topological class can be separated in a post-processing filtering step using the convolution to a bank of filters and morphological operations.

Our weighted loss (labelled Uadapt) has been tested to segment pulmonary structures in CT scans using a simplified 2D UNet, illustrated in figure 1.

Lung structures were labeled as cylinder (body), sphere (lungs), tube (vessels and bronchi) and an unknown unstructured class for the background. Vessels were separated from bronchi in the tube class using the tubular filtering for vessel detection described in [2]. The CT scans were acquired at Hospital de Bellvitge from 21 patients (with 4 CTs for each patient) [2], available at http://iam.cvc.uab.es/downloads/.

For comparison purposes we also trained the same UNet with multi-organ (body, lung, bronchi, vessels and unknown) loss with constant weights, labelled Uconst, and the weights adaptation described in [1], labelled USudra. All networks were trained from scratch using 2D slices uniformly sampled from the volumes of 14 patients during 450 epochs. The 4 scans of the remaining 7 patients (28 cases in total) were used for testing. Testing volumes were processed slice by slice to obtain a 3D volume and 3D segmentations were assessed using precision, recall and dice. Ground truth was defined from manual editing of the segmentation of lung structures described in [2].

Figure 2 shows DICE box plots for the 4 anatomical structures (lung, body, bronchi and vessel) and the 3 losses. Table 1 reports the statistical summary (mean +/- standard deviation for the test volumes) for each quality score and loss function. The adaptive weights loss described in [1] is the worst performer (with even some missing structures), probably due to a poor convergence arising from its highly non-linearity. Our Uadapt increases recall of both minority structures, especially bronchi. However, for the latter, precision also drops, which results in a dice similar to Uconst. Given that the ranges for precision in the detection of tubular structures are 0.9+/-0.02 with the same recall, we attribute the drop in bronchi precision to the post-processing used to split the tubular class, which uses classic filters highly sensitive to vessels. This also explains the substantial increase in vessels's DICE score.

Our experiments show that grouping organs into topological types in a multi-shape approach using a weighted loss with weights adapted for each training sample can alleviate class imbalance. Our immediate work will focus on improving the splitting of each topological type into the different organs using a convolutional neural network.

[1] Sudre C, Li W, Vercauteren T, Ourselin S, Cardoso M (2017) Generalised dice overlap as a deep learning loss function for highly unbalanced segmentations. Deep learning in medical image analysis and multimodal learning for clinical decision support (2017):240-248.

[2] Gil D, Sanchez C, Borras A, Diez-Ferrer M, Rosell A (2019) Segmentation of distal airways using structural analysis. Journal PloS one (14):12

Figure 1. The simplified UNet architecture.

Figure 2. Dice box plots.

fig. 1

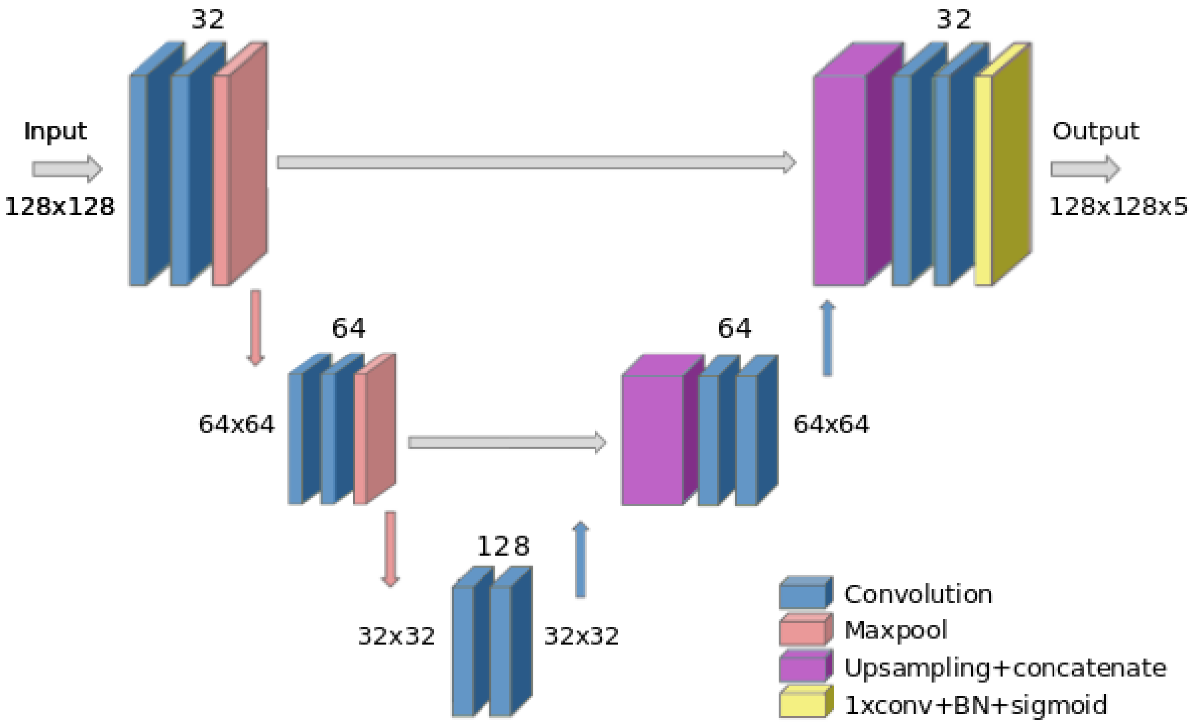
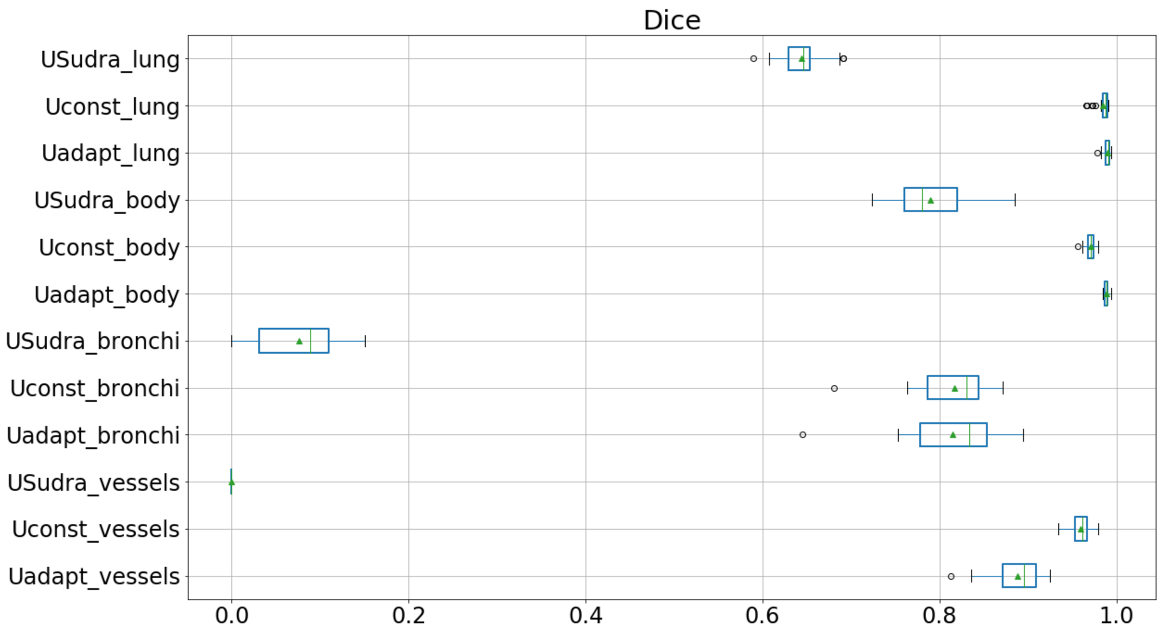


fig. 2



tbl.1
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