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Yohan Payan & Lucie Bailly

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# Deep learning for bone segmentation: towards automating failure load simulations

E. Saillard<sup>a</sup>, M. Gardegaront<sup>a,c</sup>, F. Bermond<sup>c</sup>,  
D. Mitton<sup>c</sup>, J.-B. Pialat<sup>b,d</sup>, C. Confavreux<sup>d</sup>,  
H. Follet<sup>a</sup> and T. Grenier<sup>b</sup>

<sup>a</sup>INSERM, LYOS UMR 1033, Univ Lyon, Lyon, France;

<sup>b</sup>INSA-Lyon, CREATIS, UMR5220, Univ Lyon, Villeurbanne,

France; <sup>c</sup>Univ Eiffel, LBMC UMRT9406, Univ Lyon, Lyon, France;

<sup>d</sup>Hospices Civils de Lyon, France

## 1. Introduction

Bone segmentation is an important step in performing biomechanical simulations on in-vivo CT data as it is a mandatory step to obtain meshes needed for numerical simulations. Segmentation can be a tedious task when done manually, and expert segmentations are subject to intra-operator and inter-operator variability.

Nowadays, deep learning approaches can perform this image segmentation task automatically (Aljabri and AlGhamdi 2022). These approaches must be trained on many images to guarantee a minimum of generalization to new images. However, it is not always possible to have many images with their manual segmentations. It is then necessary to use training techniques to make the best use of the available data.

In this paper, we propose a dedicated pipeline of pre-processing, deep learning-based segmentation and post-processing for human femurs and vertebrae segmentation of CT-scans volumes.

For both tasks, we experimented with three U-Net architectures and showed that out-of-the-box models enable automatic and high-quality volume segmentation, if carefully trained.

## 2. Methods

In this section, we first detail the database used for the two segmentation tasks, then the preprocessing developed to ensure the deep learning networks trains correctly (architectures used presented in section 2.3).

### 2.1. Datasets

For the femur segmentation task, we used our in-house MEKANOS dataset that consists of eleven CT-scans of hips, where both femurs are present. Those scans were acquired in clinical routine following a standard procedure (axial slice  $512 \times 512$  pixels, slice thickness 0.7 mm) and with different manufacturer acquisition systems. Some femurs have metastatic osteolytic lesions which complicate the segmentation task. For this database, 11 3D manual segmentations are available, corresponding to 18 femurs. 12 femurs were used for training, 4 for validation and 2 for testing.

For the vertebrae segmentation task, we used two publicly available datasets: VerSe2019 and VerSe2020 (Sekuboyina 2021). Those datasets contain 374 CT-scans of various sizes all with manual segmentation. The number of vertebrae on each scan ranges from 3 to 25, with all types of vertebrae present in the dataset. In this study we retained 368 patients who do not have additional transitional T13 scanned. 246 scans were used for training, 62 for validation and 60 for testing.

### 2.2. Pre-processing pipeline

For femur segmentation, we propose a fully automated pre-processing pipeline to facilitate the deep learning training. This consists in transforming the scans with two femurs into separate femur volumes with the same orientation, and then obtain the resolution and intensity range for all volumes. This pre-processing task is done in several steps (Figure 1). It allows to increase the size of the dataset: all femurs

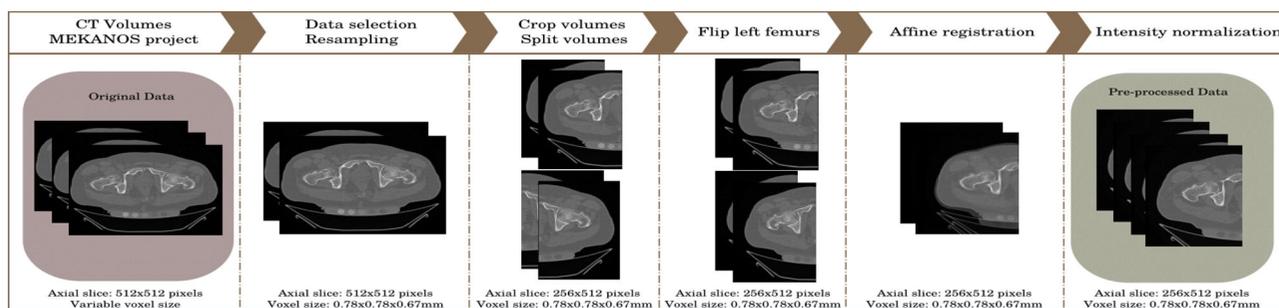


Figure 1. Pre-processing pipeline proposed for femur segmentation.

are seen as right femur. Then, the intensity values of these volumes are clipped and normalized from 0 to 1.

### 2.3. Neural networks

We used several convolutional neural networks all based on the U-Net architecture (Aljabri and AlGhamdi 2022). We implemented a 2D multi-planar U-Net, as well as a 3D U-Net. We compared the results with nnUNet, the state-of-the-art convolutional neural network for medical image segmentation (Isensee 2021).

Three 2D-Unet were trained on axial, coronal and sagittal slices. The 3 resulting segmentations were then fused using majority voting. The 3D-UNet model was trained using random patches of size  $64 \times 64 \times 64$ . 2D and 3D UNets were trained using Adam optimizer ( $\beta_1 = 0.9$ ,  $\beta_2 = 0.999$ ) and a DICE loss, for 250 and 500 epochs respectively, with a learning rate  $\alpha = 2 \times 10^{-4}$ , a batch size of 16 and 34.5M parameters total for 2D-UNet,  $\alpha = 3 \times 10^{-5}$ , a batch size of 4 and 12M parameters for 3D-UNet. Data augmentation, such as random rotations, translations, shearing and scaling was used to prevent overfitting. We also added morphological post-processing operations to remove small unwanted islands. The nnUNet architecture used is the '3d-fullres', with patch sizes automatically selected and default parameters. The optimizer used is SGD with an initial learning rate of 0.01. The batch size was set to 2 for both trainings, with a total number of parameters of 30.8M for femur segmentation and 31.2M for vertebrae segmentation.

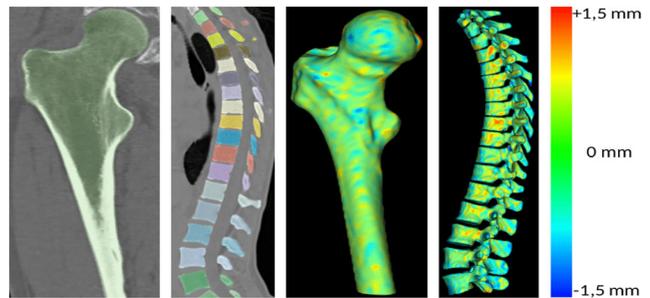
### 3. Results and discussion

To quantify the results, we used the Sørensen-Dice score (noted DSC) to evaluate the similarity between the ground-truth and the automatic segmentations ( $[0;1]$  where 1 is the best), as well as the Hausdorff distance (noted HD) to evaluate the maximum errors of the automatic segmentations (in mm, smaller the better). All metrics are computed on 3D volumes. We used a 5-fold cross-validation to quantify more accurately the results.

As shown in Table 1, the DSC obtained for both tasks exceed 0.9 which are good segmentation performance when our pre-processing is used. The results also show that U-Net 3D and nnUNet outperform the multi-axial 2D-UNet for the femur segmentation task. U-Net 3D and nnUNet perform very similarly on this task, with only a slight improvement of HD for U-Net 3D. Our femur segmentation

**Table 1.** Segmentation results obtained with our different models.

Task/Dataset	Algorithm	DSC	HD (mm)
Femur segmentation MEKANOS database	U-Net 2D multi axial No pre-processing	$0.74 \pm 0.085$	$49.86 \pm 12.57$
	U-Net 2D multi axial	$0.93 \pm 0.011$	$2.3 \pm 0.82$
	U-Net 3D	$0.96 \pm 0.008$	$2.2 \pm 0.71$
Vertebrae segmentation VerSe database	nnUNet 3d_fullres	<b><math>0.96 \pm 0.006</math></b>	$2.4 \pm 0.84$
	nnUNet 3d_fullres	<b><math>0.88 \pm 0.016</math></b>	<b><math>19.74 \pm 9.45</math></b>



**Figure 2.** Automatic segmentations obtained with nnUNet(left), pixels distance to the ground-truth(right).

pipeline shows results comparable to state-of-the-arts methods (Liang 2021), and our vertebrae segmentation method shows results similar to the best methods using the VerSe datasets (Isensee 2021).

For vertebrae segmentation, nnUNet proved very efficient, but the HD is much higher, due to small mislabelling of some vertebrae. Figure 2 shows results obtained with our approach and the errors made when comparing to experts. The proximal part of the femur is more prone to segmentation errors than the distal part, but inaccuracies remain minimal. For vertebrae segmentation, the vertebral body and pedicle are less likely to be mislabelled or mis-segmented than the spinous or transverse process, where the delimitation between 2 vertebrae is more difficult to assess.

The total training time is 12 h for 2D-UNet per axis, 16 h for 3D-UNet and 48 h for nnUNet on the femur dataset. This substantial difference is also present during inference, where nnUNet takes 30 min for a prediction when standard models only take 3 min.

### 4. Conclusions

In this paper, we proposed a dedicated pre-processing pipeline for femur segmentation as well as deep learning based segmentation methods for femurs and vertebrae segmentation. From our experiments, we showed that it is primordial to use pre-processing in order to improve the segmentation results. U-Net architectures are efficient and can serve as primary tools to perform automated bone segmentations. The

results obtained allow us to envision the use of this approach in a broader pipeline in biomechanical simulations on patients with metastatic lesions.

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 thomas.grenier@creatis.insa-lyon.fr