Automated L3-based sarcopenia quantification in CT scans

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Abstract

Sarcopenia refers to a skeletal muscle disorder that results in gradual and widespread muscle loss. Single-slice sarcopenia quantification is done with the localization of a vertebra first, followed by muscle segmentation. In this paper, we present a fully automated sarcopenia assessment pipeline for CT scans, relying on powerful deep learning based techniques. Our framework consists of two steps, one that solves the detection of the appropriate CT slice using reinforcement learning and one that addresses the segmentation of the abdominal muscle mass together with the total quantification of its area. Our pipeline has been evaluated on 100 patients, including different CT scan protocols, and reports an overall quantification performance smaller than the interobserver, indicating its potential for clinical practice.

Keywords: Sarcopenia, muscle loss, deep reinforcement learning, deep learning.

1. Introduction and Background

Over the past few years, sarcopenia quantification has gained significant interest especially since it has been shown to be linked to outcomes of cancer treatment. Previous works have indicated that sarcopenia is a strong marker for response to chemotherapy, immunotherapy or surgery (Bozzetti, 2017). Computed tomography (CT) is probably the best technique to assess muscle mass and quality and it is considered the gold standard method of body composition analysis. The most common way to assess skeletal muscle mass uses the cross-sectional areas of the psoas and the abdominal muscles at the level of the third (L3) or fourth (L4) lumbar vertebra. In this study, we focus on L3-based sarcopenia assessment, however this same technique can be applied to other thoracic or lumbar vertebrae levels. In clinical practice, the L3-based sarcopenia assessment is done in three steps. First, the radiologist identifies the slice passing by the middle of the third lumbar vertebra. On the axial view of the selected slice, the radiologist then segments the psoas as well as the parietal muscles. Finally, this segmentation is used to compute a skeletal muscle index (SMI) score. This three-step process is quite tedious, time-consuming and error-prone. A computer-based diagnosis tool is therefore essential. In this paper, we present a novel and reliable way to compute the sarcopenia assessment fully automatically. For slice localization, we leverage a deep reinforcement learning algorithm. We then rely on a U-Net like architecture for muscle segmentation. Our fully automatic pipeline is trained and compared against expert radiologists.

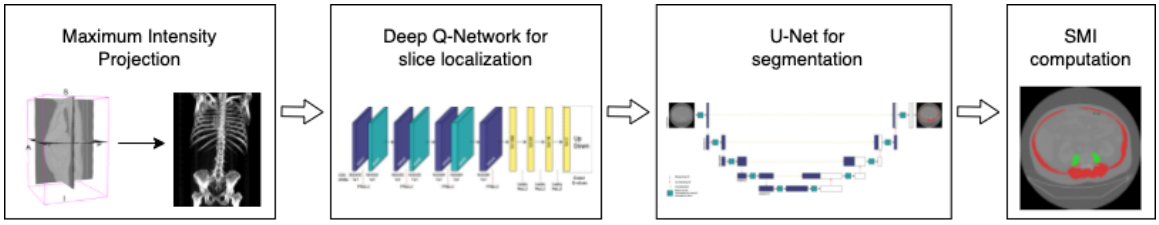

Figure 1: Overall pipeline for sarcopenia assessment, presented in this study. The CT scan is compressed using a MIP projection and given to a deep reinforcement learning architecture for slice detection. Using the detected slice, a U-Net like architecture is used to segment the muscles on which the SMI computation is performed.

2. Automatic Sarcopenia Assessment

For slice localization, since the input of our problem is 3D and output is 1D (z-axis), we reduce our input dimensionality using a frontal maximum intensity projection (MIP) technique that converts a 3D volume to a 2D image, keeping the entire body structure. We formulate the slice localization problem as a *Markov Decision Process* (MDP), which contains a set of states S, actions A, and rewards R as defined in Laousy et al. (2021) and train a Deep Q-Network (DQN) and Duel-DQN network.

The next step after localization is segmentation. We use a U-Net network in order to segment the psoas and parietal muscles. The segmentation areas are then used to compute the skeletal muscle index. We first pre-process the images by resampling them to 512×512 with a spacing of $1mm^2$. Pixel values are then clipped to [-150,300] and min-max normalized to [0,1]. Our 2D U-Net is composed of four depth layers. For each resolution, a block of layers contains: 3 convolution layers with a filter of size 3 followed by a ReLU activation layer. The Adam optimizer was used with a learning rate of 10^{-3} and a linear adaptive learning rate scheme, using a Dice similarity coefficient (DSC) loss for the training. For both tasks, we randomly selected 900 patients for training and validation, and 100 for the test set on which we have annotations from two expert radiologists.

3. Results

We evaluated each block of our pipeline independently and combined both on a final evaluation. As for the localization task, we compared our technique to two other vertebra localization methods. Kanavati et al. (2018) uses a fully convolutional neural network that outputs a 2D confidence map around the vertebra area. Payer et al. (2020) addresses the more general problem of multiple vertebrae localization and segmentation and uses a combination of 3 different U-Net like networks. The error is calculated as the distance in millimeters (mm) between the predicted L3 slice and the one annotated by the experts. Results are reported in Laousy et al. (2021). We notice that our proposed deep reinforcement learning approach achieves better detection results more particularly on scarce data settings. For muscle segmentation, our U-Net achieves a DSC of 0.93, which is comparable to other published studies (Graffy et al., 2019). Regarding the end-to-end pipeline evalu-

Table 1: Evaluation of the different steps of the pipeline in comparison with the interobserver.

	Localization (mm)	**Segmentation** (DSC)	**SMI difference** (cm^2)
Interobserver	2.04	0.95	6.12
Proposed	3.77	0.93	5.06

ation, we execute on the test set both the slice localization followed by the segmentation. We then compare the computed total psoas and parietal areas in cm^2 to the ground truth. We obtain a difference of 5.06 cm^2 (representing only 0.3% of the total surface of the axial view). Overall, our method achieves a smaller SMI difference than the one reported by the expert radiologists, highlighting the potential of our technique to be adopted in clinical practice to facilitate sarcopenia assessment.

4. Conclusion

This study indicates that the use of both deep reinforcement learning and deep learning for localization and segmentation is effective and promising in sarcopenia assessment. The exposed method can be extended to any slice-based sarcopenia assessment technique on T4, T5, T12 or L4 vertebra levels. In the future, we plan to explore end-to-end learning strategies to perform both steps simultaneously.

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