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TEZĂ DE DOCTORAT

# Advances in automatic multi-organ segmentation

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# ABSTRACT

The doctorate thesis contains original research in the field of automated medical segmentation in a multi-organ setup.

Interpretation of human computed tomography (CT) or magnetic resonance imaging (MRI) by medical practitioners is a complex and time-consuming activity. Furthermore, the organ shapes and sizes are diverse and there are large variations between different individuals, which makes the training of human experts a long running and costly process. Thus, the capability to automatically extract information from medical images has a huge potential in radiology and it might alleviate the issues that practitioners encounter in their day-to-day activities.

In order to advance the research field, I have designed and implemented architectures that either alleviate known issues of modern methods or that present completely new algorithms that perform organ segmentations. I have also set the target to utilize the proposed solutions in multi-organ setups to expand their attractivity and usage potential in productive systems.

The work started by doing a comprehensive review of the existing techniques. Machine Learning (ML) models are the most used in automated segmentation, as they currently provide the best results. Therefore, the first chapter details Deep Learning (DL) methods that were significant in the development of the multi-organ segmentation field. It contains a comprehensive list of solutions based on supervised deep-learning algorithms like Convolutional Neural Networks (CNNs) and Fully Convolutional Neural Networks (FCNs). It also describes hybrid architectures, that employ either Recurrent Neural Network (RNNs), or Generative Adversarial Networks (GANs) or approaches that cannot be categorized in one of the above. Lastly, Deep Reinforcement Learning (DRL) approaches are also detailed, as these have gained renewed interest in the last years.

**Chapter 2** describes an original architecture that is used for thoracic multi-organ segmentation. Its aim is to prove that even when using lower hardware resources (available to most researchers worldwide), a good design can still produce accurate results. The DL architecture is built using the standard U-Net algorithm, but it employs modern pre-processing techniques, a smart batching mechanism and fusion of results from several organ networks. There are four single organ networks and a multi-organ network, and their results are combined for a final automatic segmentation. The maximum available GPU memory is 8 GB, therefore the design can be replicated by most researchers and it adheres to the low resource constraints. The architecture was tested on the dataset provided by the SegTHOR challenge, which has an automatic ranking system based on un-labeled test data. The method achieved the 8$^{th}$ place in the international challenge, demonstrating its capability to yield results comparable to other cutting-edge algorithms.

In **Chapter 3** a totally new and original architecture is presented. The status quo in automatic segmentation is that the best results are achieved by employing fully supervised DL algorithms. I challenged this by implementing an architecture that uses Deep Reinforcement Learning to produce results on par with modern architectures. The segmentation process was successfully translated into a Markov Decision Process (MDP) problem, by using the slice of a CT as the environment and training an agent who will move inside the image in order to delineate a human organ (namely, the heart). Inspired by the Deep Q-Network (DQN) algorithm, I implemented an agent which navigates through a slice of a CT and employs discrete actions (move right, left, up, down and segment organ) to

execute the segmentation. It is rewarded based on his actions and in this way, it will learn the optimal policy to fulfill its tasks.

Because the segmentation is too complex for a single agent to handle, the complete architecture consists of pipeline, that starts with a pre-processing step, continues with the detection for the presence of an organ in the slice, employs an DQN agent that detects a starting position for the segmentation, and finishes with an DQN agent that does the organ segmentation. The rewards are based on how good each selected action is, and the segmentation agent is also incentivized to generate closed contours (as most human organs are). The results demonstrate that DRL solutions can be deployed also for the automatic segmentation task and that they can be generalized with good results even when trained on a limited number of data (e.g., 10 human CTs).

**Chapter 4** expands the DRL implementation with the usage of a more modern algorithm, namely Proximal Policy Optimization (PPO). The architecture is still a pipeline comprised of the pre-processing step, detection for the presence of an organ in the slice, an DQN agent that detects a starting position for the segmentation, but for the segmentation agent it will deploy a PPO agent that uses continuous actions to delineate the organ. The output values will represent the edge of the organ, so there is no need to perform a lot of actions to navigate in the slice. There are several implementations, with a variant that used two PPO agents (one for organ left side segmentation, and one for the right side) and another variant in which a single agent will output value pairs to delimit both organ's edges. The results are comparable to the DQN architecture, but the training of the agents is very fast (a couple of hours) therefore it can quickly be adapted to other organs.

**Chapter 5** presents the deployment of the PPO architecture for several other organs, demonstrating that it can be used in a multi-organ setup. I have utilized another dataset and selected two very different organs, in order to better test the methods. The first selection was the pancreas, who is a very small organ. On the opposite end, the second one was the liver, who is very large and has a diverse morphology across the imaging layers. The results proved that DRL agents can successfully segment different organ types.

**Chapter 6** contains additional improvements to the DRL architectures. The main drawback of the initial designs was the need to include more sub-components and more agents in a pipeline. In order to alleviate this, the goal of the research was to design agents that are able to segment organs in a single run and with as little external help as possible. Therefore, I implemented new agents with enhanced algorithms and proposed simplifications that make the agents learn faster and make them less complex to be utilized. Lastly, I presented a new design that decreased the required number of agents, and which greatly simplified the pipeline's structure.

**Chapter 7** outlines the final conclusions and summarizes the research artifacts. It also presents the personal contributions and the dissemination of the results.