Segmentation of 3D vascular networks: a review

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Abstract

Blood vessel segmentation in 3D medical images is important in several clinical practices, and its automation has been studied during the last decades. However, the current algorithms are still prone to segmentation errors, such as missing segments or an inadequate merging or splitting of branches. These errors may severely change the topology of the network, risking the success of future medical interventions that depend on it. This paper presents a review of the state-of-the-art machine learning algorithms for the automatic segmentation of blood vessels in 3D medical images, while also giving special focus to the topology coherence of the segmented blood vessel networks.

1 Introduction

Blood vessel 3D segmentation is a highly relevant topic in medical image analysis, being crucial for the diagnosis and prognosis of clinical outcomes in different fields. However, manual segmentation of blood vessels is a hefty and time-consuming procedure, lacking repeatability even for the most experienced clinicians [8]. One way to help clinicians during the segmentation processes is to create automatic or semi-automatic Machine Learning (ML) algorithms capable of segmenting blood vessels. This paper aims to provide relevant and updated information regarding the state of the art for 3D blood vessel segmentation, while also proposing possible implementations of said technologies. It also focus on the generalization and topological coherence capabilities of these algorithms. The paper is organized as follows: Section 2 contains a literature review that exposes the state of the art within different fields of 3D blood vessel imaging, while Section 3 summarizes the information gathered during the paper.

2 Literature Review

The advancements made in the field of automatic segmentation of blood vessels in 3D medical images are due to the combination of various technological and scientific fields. This section reviews the state of the art of some of those fields, namely the most recent ML algorithms, the most used 3D imaging modalities, and examples of possible datasets to train and test the ML algorithms.

2.1 Machine Learning Algorithms

Even though many ML algorithms have been developed for 3D vascular network segmentation, there is no record of an algorithm that could flawlessly identify every component of complex blood vessel trees. In an attempt to increase topological coherence, Araújo *et al.* [2] proposed the addition of a refinement step at the end of a typical segmentation network. Using a variational auto-encoder, it was possible to predict more correct paths and less infeasible paths, without penalizing the Area Under the Curve (AUC).

Recently, Su *et al.* [11] utilized a deep reinforcement learning approach for centerline tracking and bifurcation detection, with the intent of extracting the cerebral anterior vessel tree of patients with an intracranial large vessel occlusion, achieving a median recall of 68 % and precision of 70 %. Cervantes-Sanchez *et al.* [4] developed an algorithm for the automatic segmentation of coronary arteries, based on a multiscale analysis performed by using Gaussian filters in the spatial domain and Gabor filters in the frequency domain. The results of the multiscale analysis were then used as inputs by a multilayer perceptron for the enhancement of vessel-like structures.

In order to predict the occurrence of cerebral vasospasms, Capoglu *et al.* [3] used sparse dictionary learning algorithms with covariance-based features in order to encode the whole 3D vessel structure in a vector of fixed size. As shown by the performance of the model, it was concluded that 3D image data could be sufficient for vasospasm prediction (AUC = 0.93). Furthermore, Alhussein *et al.* [1] used unsupervised learning algorithms, which combined an Hessian based approach and an intensity transformation approach to segment retinal vascular networks, with a special focus on image de-noising and identification of thin vessels.

When segmenting head and neck 3D blood vessels, Fu *et al.* [5] developed CerebralDoc, an algorithm based on a 3D convolutional neural network, achieving an accuracy of 0.931. The model was optimized by a bottleneck-ResNet which helped to maintain topological coherence, avoiding segmentation errors associated with partially missing blood vessels. In turn, Xia *et al.* [12] propose a generic neural network for the segmentation of vessel-like structures in different modalities of 3D medical imaging. They used a feature selection module to select discriminative features from an encoder and decoder simultaneously, which aimed to increase the weight of edge voxels, thus significantly improving the segmentation performance. Table 1 displays the organs targeted in each paper referred in this subsection.

Table 1: Referred authors and their target organs for study.

Authors	Year	Organs
Su *et al.* [11]	2023	Brain
Xia *et al.* [12]	2022	Various Organs
Fu *et al.* [5]	2020	Head and Neck
Alhussein *et al.* [1]	2020	Eye (Retina)
Hajhosseiny *et al.* [7]	2020	Heart
Araújo *et al.* [2]	2019	Eye (Retina)
Capoglu *et al.* [3]	2019	Brain
Cervantes-Sanchez *et al.* [4]	2019	Heart
Rozeman *et al.* [9]	2017	Cervical Vertebrae

It is important to note that the evaluation metrics used to assess each algorithm may differ from study to study, which makes it difficult to compare the relative performance of different algorithms. A way to homogenize the evaluation metrics is to consider the works developed for contests such as the "Grand Challenges for Medical Image Analysis", since the same performance measures are used in every algorithm [10].

2.2 3D Medical Imaging

Regarding the utilization of 3D medical imaging for blood vessels identification, it is important to note that there is no global golden standard, and the optimal imaging modality varies accordingly with the target organ. Some of the most popular modalities are the Magnetic Resonance Angiography (MRA) [7], Duplex Ultrasonography [9], and Computed Tomography Angiography (CTA) [6]. Table 2 displays the imaging techniques used in some studies mentioned in this paper.

Nowadays medical imaging collection does not suffice to circumvent the limitations found during vessel segmentation, namely the low signal-to-noise ratio, proximity between image resolution and the diameter of some smaller vessels, or even the reliability of the topological properties

Table 2: Referred authors and the imaging modalities used in their studies

Authors	Year	Imaging Modalities
Su *et al.* [11]	2023	CTA
Xia *et al.* [12]	2022	Various Imaging Modalities
Alhussein *et al.* [1]	2020	Fundus Photography
Hajhosseiny *et al.* [7]	2020	MRA
Fu *et al.* [5]	2020	CTA
Martinéz *et al.* [6]	2020	Various Imaging Modalities
Araújo *et al.* [2]	2019	Fundus Photography
Capoglu *et al.* [3]	2019	3D Brain Angiogram
Cervantes-Sanchez *et al.* [4]	2019	X-Ray Angiography
Rozeman *et al.* [9]	2017	Duplex Ultrasonography

of the vascular networks, given that even the best performing methodologies do not normally penalize missteps such as incomplete connections between segments, producing segmentations with incorrectly disconnected networks. This is particularly relevant in graph-like structures, such as blood vessel networks, which might put at risk all the clinical steps that follow the segmentation task.

2.3 Datasets

Most of the published works rely on in-house datasets, and only a few of those datasets are accessible or partially accessible to the public, sometimes containing an insufficient amount of images for benchmarking. Some of the most crucial aspects of ML are the quantity, quality and variability of the data used to train and validate the developed algorithms. The access to this data is facilitated by entities such as the "Grand Challenges for Medical Image Analysis", which strives to evaluate new algorithms from different authors using the same set of test images and performance measures. An example of a dataset provided by this entity is the VESSEL12, containing annotations made by health professionals and formed with the intent of evaluating vessel segmentation algorithms [10].

Datasets sometimes do not contain a sufficient amount of data, or have input distribution shifts among one another, (*e.g.*, percentage of pixels that are vessels may be higher or lower, the distribution of intensities may also differ). Domain adaptation can be a powerful tool in these situations since it can transfer knowledge from a foreign dataset containing labelled data into the dataset of interest, which has insufficient labelled data. Recent approaches consist of using an Asymmetrical Maximum Classifier Discrepancy for unsupervised domain adaptation, or a Semi-Supervised Cross-Anatomy Domain Adaptation [13].

3 Conclusion

During this paper it was shown that ML algorithms can decrease the necessary time to complete the blood vessels segmentation process by automating it, while at the same time leaving the possibility of human experts' intervention. To achieve better results for 3D blood vessel segmentation and topological coherence, future algorithms should focus on 3 main characteristics:

1. The capability to detect vessels with low Signal-to-Noise Ratio, low caliber and high tortuosity (*e.g.*, near the equipment resolution), and have a good performance discerning true positives from false positives;

2. Incorporate the concepts of domain adaptation and transfer learning in order to better leverage the knowledge extracted from vascular networks of different anatomical regions;

3. Promote and evaluate the topological coherence between the ground truth and the predicted masks, penalizing topological errors according to the place in which they occur;

When choosing the most adequate method of ML, a critical decision point is the amount of available labelled data. High amounts of labelled data tend to favour a supervised approach, while the shortage of labelled data tends to favour unsupervised learning.

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