View Reviews

Paper ID
1526

Paper Title
Self-Supervised Vessel Enhancement Using Flow-Based Consistencies

Reviewer #1

Questions

2. Please describe the contribution of the paper (a few lines)
This paper proposes a novel self-supervised training method that is designed for vascular structure segmentation. The method is applicable for many tubular structures. The efficacy was validated with several kinds of open datasets including 2D retinal vessel, 3D CT / MRI. The performance comparisons with the conventional methods show that the proposed method can achieves higher scores in DICE metrics.

3. Please list the main strengths of the paper; you should write about a novel formulation, an original way to use data, demonstration of clinical feasibility, a novel application, a particularly strong evaluation, or anything else that is a strong aspect of this work. Please provide details, for instance, if a method is novel, explain what aspect is novel and why this is interesting.
Novel formulation: The method models vessels with a few parameters of template image, radius, flow direction, and so on. The U-net like neural networks are trained to predict those parameters without labels by minimizing the similarity loss (Normalized cross correlation) between the training image and the predicted image.

Segmentation performance: The advantage of the method is that the method can achieve a high DICE score without labels, since it can model tubular structure's thickness or extent, compared to the conventional methods. A wide range of vascular applications regarding volumetry purposes would benefit from this research.

4. Please list the main weaknesses of the paper. Please provide details, for instance, if you think a method is not novel, explain why and provide a reference to prior work.
It is not clear that the method is also applicable for diseased vessels with different appearances, for instance clogged vessels with soft / hard plaques. The method seems to fail segmenting such vessels, because it uses a template image representing an ideal vessel (disk/tube).
Centerline detection performance is not improved significantly.

5. Please rate the clarity and organization of this paper
Good

6. Please comment on the reproducibility of the paper. Note, that authors have filled out a reproducibility checklist upon submission. Please be aware that authors are not required to meet all criteria on the checklist - for instance, providing code and data is a plus, but not a requirement for acceptance
The idea is clearly given in the paper. The reproducibility seems relatively high. Furthermore, the authors show wills to provide the codes in public.

7. Please provide detailed and constructive comments for the authors. Please also refer to our Reviewer's guide on what makes a good review: https://miccai2021.org/en/REVIEWER-GUIDELINES.html
The approach is unique, but its potential is limited by using a few parameters and single template image. It is interesting to provide the authors's opinions about using multiples template images, or trainable (parameterized) template.

8. Please state your overall opinion of the paper (visible to authors).
Probably accept (7)

9. Please justify your recommendation. What were the major factors that led you to your overall score for this paper?

The paper proposes a novel and general approach for vascular structure segmentation. A wide range of vascular applications would benefit from this work.

10. What is the ranking of this paper in your review stack? Use a number between 1 (best paper in your stack) and n (worst paper in your stack of n papers).

1

11. Number of papers in your stack

5

12. Reviewer confidence

Very confident

Reviewer #2

Questions

2. Please describe the contribution of the paper (a few lines)

Propose a self-supervised method for vessel segmentation taking consideration of tube-like structure properties such as connectivity, profile consistency, and bifurcation. It is generalizable across modalities.

3. Please list the main strengths of the paper; you should write about a novel formulation, an original way to use data, demonstration of clinical feasibility, a novel application, a particularly strong evaluation, or anything else that is a strong aspect of this work. Please provide details, for instance, if a method is novel, explain what aspect is novel and why this is interesting.

Claimed to be first unsupervised deep learning method that takes a raw image
as input and outputs per-pixel vessel statistics as output.
A clever way to incorporate vessel properties in the design but not directly as hand crafted features.
Comprehensive evaluation on multiple datasets, both 2D and 3D, with multiple modalities.

4. Please list the main weaknesses of the paper. Please provide details, for instance, if you think a method is not novel, explain why and provide a reference to prior work.

Unclear descriptions on key components, causing confusions for readers.
Possible design flaw for the loss.
Unclear value of this method compared with existing supervised methods which have much better performance

5. Please rate the clarity and organization of this paper

Satisfactory

6. Please comment on the reproducibility of the paper. Note, that authors have filled out a reproducibility checklist upon submission. Please be aware that authors are not required to meet all criteria on the checklist - for instance, providing code and data is a plus, but not a requirement for acceptance

Public dataset. No link for their code provided in the manuscript.

7. Please provide detailed and constructive comments for the authors. Please also refer to our Reviewer's guide on what makes a good review: https://miccai2021.org/en/REVIEWER-GUIDELINES.html

There are three directions at a bifurcation where one larger branch splits into two smaller branches. Since the larger branch is unknown in prediction, how can ensure the two vectors (b1, b2) are exactly pointing to the smaller branches? In other words, without special constraints on branch sizes, u, b1 and b2 are interchangeable during prediction.
Assuming vessel profile as a unit disk, and use it to match the profiles along the artery might not cover the abnormal situations when for example, at bifurcation, artery is stenotic or there are flow artifacts.
Profiles at opposite directions should be the same, so the matching with the template Lm should also be the same. In the absence of bifurcation, why b1(p)=b2(p)=-u(p) minimizes the loss, b1 b2 can also be the same as u?
Fig 1 is the most important figure in this paper, but it is misleading. 1) fΘ() is misleading. You used a U-Net here,

but the plot looks like fΘ() is an encoder only. The final network output size needs to be mentioned, which is the same size as the image input? 2) the plot for r is also misleading. It should have a radius for all the pixels. But the image shows grid-wise small radius predictions on backgrounds and non-grid radius on arteries. Why r on artery region can be at non-grid positions exactly on the artery centerline? How did you deal with overlapping radius predictions (for arteries with more than 1 pixel thickness). 3) r map has a much wider gap than u map, b map has a much wider grid than u map. Are the output sizes really the same?
There is a lack of information for the bifurcation loss, causing my many confusions about your design, although there is an ablation study to prove its usefulness. 1) There seems a lack of constraint for b1 and b2 to be different from u. For the cases with bifurcations, b1 and b2 can still be the same or opposite directions with u to minimize the loss. If u is at the larger branch, and it bifurcates into b1, b2 two smaller branches, Lm(b,r;I,T) is even smaller when b=+-u. 2) the radius r used for three Lm calculations is the same? If that is the case, it is unfair for the similarity metric calculation on b1, b2. As the real radius for branched out arteries are much smaller than the radius at the bifurcation. 3) the cause of the performance improvement using bifurcation loss is really from taking advantage of the bifurcation structure? Or this is just because of a heavier weight on Lm loss. As the majority of the pixels are not bifurcations. The final total loss is more close to (1+ λ2) Lm+ λ1Lf. The ablation study should not just taking λ2 Lb away, but rather comparing with (1+ λ2) Lm+ λ1Lf
The weights λi for combining three losses need more investigations, as the choice for λi might be critical. Lm directs the vector to best match the disk template, but Lf does not allow vector direction to change along the artery, which is a natural conflict requiring a careful selection of weights to find the optimal results.
Why the evaluation on segmentation is only on a manually annotated bounding boxes at bifurcation region instead of the whole image?
Fig 3 (a) why no false positives are shown? I suppose your method will have a lot of noise branches, as the current loss design does not penalize false positives. There are negative signs for Lm and Lf, so any noise detections will lead to lower losses. Is there a threshold to select valid vessels in the design?
The section of “efficacy of the representation” is unclear. 1) I am not sure what the author means for “efficacy of the representation“. 2) Faster convergence does not mean the feature representations for your model is better. 3) the authors only report their method achieves the best validation dice score, without showing quantitative/qualitative results on the test set, like table 1 and 2 and fig 3.
The potential usage of the method is unclear. The current performance on OCT image is better than traditional image processing methods, but still far away from supervised methods. If the aim is for better downstream tasks like segmentation, there is a lack of evidence that using this method as a pretrained model improves the overall performance compared with state-of-the-art supervised methods.

8. Please state your overall opinion of the paper (visible to authors).
borderline accept (6)

9. Please justify your recommendation. What were the major factors that led you to your overall score for this paper?
Interesting and explorative ideas, but lack of clear explainations and maybe flaws in design and experiments.

10. What is the ranking of this paper in your review stack? Use a number between 1 (best paper in your stack) and n (worst paper in your stack of n papers).
2

11. Number of papers in your stack
5

12. Reviewer confidence
Confident but not absolutely certain

Reviewer #3

Questions

2. Please describe the contribution of the paper (a few lines)

This article proposes an unsupervised vessel enhancement filter using self-supervised learning. This approach is based on geometric properties of the vessels such as profile consistency, connectivity and bifurcation. This approach provides three very interesting features to characterize blood vessels in the image: the vesselness (probability of a pixel to belong to a vessel), the direction of the vessels and the radius of putative vessels at each point.
Extensive experiments have been conducted both in 2D and 3D images and comparisons with classic vessel enhancement strategies have been performed.

3. Please list the main strengths of the paper; you should write about a novel formulation, an original way to use data, demonstration of clinical feasibility, a novel application, a particularly strong evaluation, or anything else that is a strong aspect of this work. Please provide details, for instance, if a method is novel, explain what aspect is novel and why this is interesting.

I thank the authors for this interesting article. Unsupervised vessel enhancement is of great interest for vascular-related clinical applications and, to the best of my knowledge, it is indeed the first unsupervised deep learning-based approach in the literature. The article is well written and the method is clearly explained. I also appreciated the extensive experiments that have been conducted on several datasets.

4. Please list the main weaknesses of the paper. Please provide details, for instance, if you think a method is not novel, explain why and provide a reference to prior work.

My main concern regards how the authors set the parameters of the compared methods. This can dramatically affect the comparison results. I am surprised by the results obtained for Frangi in Figure 3 (d). The Frangi filter usually yields many false positives due to border issues or close curvilinear structures. However, in the results shown on Figure 3 (d), the errors seem to come from a large overestimation of the size of the structures, as well as from detections of large structures that are not curvilinear at all. I am not used to seeing that in Frangi results. In Figure 4 in the supplementary materials, Frangi detects bright structures whereas the structures of interest are dark. Normally by choosing the sign of the eigenvalues and the contrast parameter correctly this should be prevented. The optimization strategy for setting the parameters of the compared methods should be explained to convince the reader that a fair comparison was performed.

5. Please rate the clarity and organization of this paper

Very Good

6. Please comment on the reproducibility of the paper. Note, that authors have filled out a reproducibility checklist upon submission. Please be aware that authors are not required to meet all criteria on the checklist - for instance, providing code and data is a plus, but not a requirement for acceptance

I think the method could be reproduced, however the authors did not provide all the hyperparameters they used (see detailed comments)

7. Please provide detailed and constructive comments for the authors. Please also refer to our Reviewer's guide on what makes a good review: https://miccai2021.org/en/REVIEWER-GUIDELINES.html

- Regarding the profile consistency, the authors should explain in more details what their resizing transform $\Phi(u,r)$ is, as it seems that this is a crucial point of the method. This transform seems to be position-dependent, as the value of r can be different for every pixel. How is it applied in practice ? How is it included in the UNet architecture ?
- In Equation 2, I do not understand why the authors specify $\dot{q}_p = u(p)$. It seems that this relation is not used in the equation nor later in the paper. If this is important, please clarify, otherwise please remove.
- It is not clear for me why $b_1(p) = b_2(p) = -u(p)$. Why is there a minus sign ? The associated sentence is also not very clear. Please rephrase it: "Note that, in the absence of bifurcation, $b_1 (p) = b_2 (p) = –u(p)$ minimizes the same loss as L_m . in the opposite direction of the vessel flow".
- The authors should specify the value of the loss hyperparameters λ_1 and λ_2 they used. I assume that the results highly depend on these parameters. Therefore, a discussion on how to set them would be interesting.
- The authors used a batch size of 1. Is this because of memory issues ? Or did they obtain the best results with this value ? Did they observe training instability ?
- The authors should consider performing cross validation to improve the statistical significance of their results.

8. Please state your overall opinion of the paper (visible to authors).

accept (8)

9. Please justify your recommendation. What were the major factors that led you to your overall score for this paper?

The method is interesting and new. Even though I am not convinced that the comparison with other methods is totally fair, I still think the approach is interesting for the community.

10. What is the ranking of this paper in your review stack? Use a number between 1 (best paper in your stack) and n (worst paper in your stack of n papers).

1

11. Number of papers in your stack

3

12. Reviewer confidence

Confident but not absolutely certain