Description of the Algorithm

Juan-Carlos PRIETO*[1], Chantal REVOL-MULLER[1], Christophe ODET[1], Maciej ORKISZ[1], and Marcela HERNÁNDEZ HOYOS[2]

[1]Université de Lyon, CREATIS; CNRS UMR5220; INSERM U1044; INSA-Lyon; Université Lyon 1, France

[2]Grupo Imagine, Grupo de Ingeniería Biomédica, Universidad de los Andes, Bogotá, Colombia

1 Description of the framework

The algorithm is based on a variational region growing approach (VRG) (Pacureanu et al., 2010). The idea is to segment the object by means of a discrete function:

$$\phi^n(x) = \begin{cases} 1, \text{for } x \in \Omega_{in} \\ 0, \text{for } x \in \Omega_{out}, \end{cases} \tag{1}$$

where Ω_{in} and Ω_{out} are the regions that correspond to the segmented voxels. The regions defined in Ω, change according to the region-based energy $J(\phi^n)$, that must be designed so that its minimum corresponds to the expected solution. At each iteration n, the voxels that are connected to Ω_{in} are tested. If the addition of those voxels decreases the energy, then they are accepted and the discrete function is updated as:

$$\phi^{n+1}(x) = \frac{1}{2}(1 - sign\left(\Delta J(\phi^{n+1})\right). \tag{2}$$

The design of the energy function is based on a vesselness criterion proposed by (Sato et al., 1997) and on the gray levels of the original image. This relation is described in the following manner:

$$\Delta J(\phi^{n+1}) = 1 - 2\phi^n\left(\Delta J_1(f, v)\right), \tag{3}$$

$$\Delta J_1(f, v) = \frac{v}{MaxV}\left(|v - \mu_{v_{in}}|^2 - |v - \mu_{v_{out}}|^2\right) + \left|\frac{f}{MaxF}\right|\left(|f - \mu_{f_{in}}|^2 - |f - \mu_{f_{out}}|^2\right), \tag{4}$$

where $MaxV$ is the maximum value in the vesselness image, $\mu_{v_{in}}$ and $\mu_{v_{out}}$ respectively are the mean values of the vesselness image voxels in Ω_{in} and Ω_{out}. $MaxF$ is the maximum value in the original image and similarly $\mu_{f_{in}}$ and $\mu_{f_{out}}$ are the respective mean values in the image for the regions Ω_{in} and Ω_{out}.

The calculation of the vesselness image is done as a preprocessing step in a multiscale framework in order to detect various vessel sizes. The value of the vesselness image for a given voxel is updated according to the larges response of the filter accross all considered scales. The eigenvalues of the best response are stored for later use.

*This work has been partly funded by ECOS Nord C11S01 and Colciencias 1204-519-28996 grants.

After this step, some seeds in the image are automatically chosen to initialize the VRG algorithm. As proposed in (Lo et al., 2010), four different criteria are used to select the initial seeds. By using the eigenvalues of the Hessian matrix where $|\lambda_1| \geq |\lambda_2| \geq |\lambda_3|$

- $\lambda_1, \lambda_2 < 0$,
- $w \geq Contrast$,
- $(|\lambda_1| - |\lambda_2|)/(|\lambda_1| + |\lambda_2|) < Tubeness1$,
- $(|\lambda_1| - |\lambda_3|)/(|\lambda_1| + |\lambda_3|) > Tubeness2$,

where $w = \sqrt{\lambda_1^2 + \lambda_2^2 + \lambda_3^2}$, $Contrast = \bar{w} + 2\sigma(w)$, while $\bar{w}$ and $\sigma(w)$ respectively are the mean value and standard deviation of w across the image. Ideally, in bright tubular structures we should have $\lambda_1 \approxeq \lambda_2$ and $\lambda_3 \approx 0$. We have therefore set $Tubeness1 = 0.1$, as this value has to be close to 0 and $Tubeness2 = 0.9$ because this value has to be close to 1. By using these criteria we select seeds that not only belong to vessels but are also centered inside them. The output of the VRG algorithm is strong dependent on the initial seeds. The mask image is used to select the seeds inside the lungs and also to limit the scope of the VRG algorithm. The maximum number of iterations of the VRG algorithm has been set to 120. For most of the datasets the solution converges before achieving this limit. On average 90 iterations were required to find the solution.

2 Limitations of the algorithm

The algorithm was executed automatically for all datasets without any user interaction. It is a general purpose algorithm designed to segment thread-like branching structures in 3D images and only some parameter values have been adjusted using the traning data from the challenge. Additional work would be necessary to cope with pathological vessels and distinguish vessels from mucus-filled bronchi.

One limitation of the algorithm is related to the computation of the vesselness image. The multi-scale calculation of the Hessian matrix and its eigenvalues for each voxel is slow and takes a large amount of memory. A 64 bit machine architecture is required with at least 12GB RAM. To complete the segmentation of the 20 datasets it took around 36h, i.e. more than 1,5h per dataset on average.

References

Lo, P., Sporring, J., Ashraf, H., Pedersen, J. J., and de Bruijne, M. (2010). Vessel-guided airway tree segmentation: A voxel classification approach. *Medical Image Analysis*, 14(4):527 – 538.

Pacureanu, A., Revol-Muller, C., Rose, J.-L., Sanchez Ruiz, M., and Peyrin, F. (2010). A vesselness-guided variational segmentation of cellular networks from 3D micro-CT. In *Proc. IEEE Int. Symp. Biomed. Imaging: from Nano to Macro*, ISBI'10, pages 912–915, Piscataway, NJ, USA. IEEE Press.

Sato, Y., Nakajima, S., Atsumi, H., Koller, T., Gerig, G., Yoshida, S., and Kikinis, R. (1997). 3D multi-scale line filter for segmentation and visualization of curvilinear structures in medical images. In Troccaz, J., Grimson, E., and Msges, R., editors, *CVRMed-MRCAS'97*, volume LNCS 1205, pages 213–222. Springer Berlin / Heidelberg.