Venous segmentation using Gaussian mixture models and Markov random fields

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Introduction:

Magnetic resonance imaging (MRI) provides a non-invasive window into the cerebral venous vasculature without the need for a contrast agent. MRI techniques that utilise phase, such as susceptibility-weighted imaging[1] (SWI) and quantitative susceptibility mapping[2] (QSM), provide additional contrast beyond standard MRI for imaging the intracranial veins. SWI is used clinically and exhibits enhanced sensitivity to smaller vessels, whereas QSM distinguishes between paramagnetic and diamagnetic substances. We introduce an algorithm for the segmentation of venous vasculature that utilises the complimentary contrast of SWI and QSM images. The algorithm is based on a combination of a Gaussian mixture model (GMM) and a novel Markov random field (MRF) that uses Gabor filters (GMRF) to enforce consistency to vessel like structures.

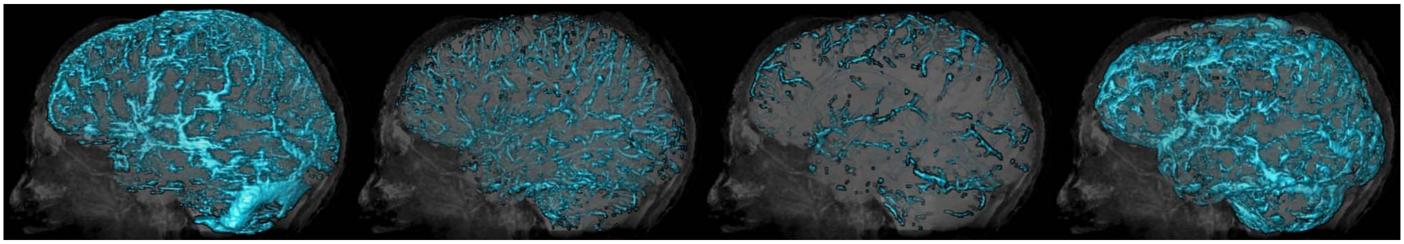

Figure 1: Render of semi-transparent SWI image with overlaid venogram. Left-to-right: ground-truth, vesselness on SWI, and on QSM, GMRF.

METHODS:

Volunteers (n=3) were scanned using a 3T Siemens Skyra with a 20-channel head and neck coil. A single echo, flow compensated, gradient-recalled echo (GRE) sequence was used (TE=20ms, TR=30ms, Voxel=0.9mm isotropic, Matrix=256x232x160, Flip Angle=15). SWI was obtained directly from the scanner (IDEA version VD13C), and k-space data saved for each coil and combined using the CSENSE algorithm[3]. Phase images were processed using HARPERELLA[4] and QSM maps were computed using STI-Suite[5]. The first-author, under the supervision of a clinical radiologist, produced the ground-truth by manually marking up the venous structures using the SWI images. GMM was used to cluster the QSM and SWI for each voxel, *i*, initially conditioned on a QSM>0.05 mask. The posterior probability from the GMM step was used as input contrast to the GMRF, σ.

$$E_{i,data} = \alpha_i(1-\sigma_i) + (1-\alpha_i)\sigma_i \quad (1)$$

$$E_{i,shape} = \Theta_1(1-\alpha_i)\max_{\arg k}\left((\alpha_{i+k}+\alpha_{i-k})e^{-\left(\frac{1-g_{i,k}}{2\Theta_3}\right)^2}\right) + \Theta_2\alpha_i \min_{\arg k}\left((2-\alpha_{i+k}-\alpha_{i-k})e^{-\left(\frac{g_{i,k}}{2\Theta_3}\right)^2}\right) \quad (2)$$

The GMRF minimises the total energy based on a data term (Eq. 1) and a shape term (Eq. 2), where α_i is the voxel label, α_{i+k} and α_{i-k} are the labels of the adjacent voxels along the orientation *k*, and $g_{i,k}$ is the response of a Gabor filter of orientation *k* on the 3x3 neighbourhood around voxel *i*. The shape term encouraged smoothness, over a set of orientations *k,* moderated by a 2D Gabor filter response of the same orientation. Exhaustive leave-one-out cross-validation was used to train the three parameters (Θ_1, Θ_2 and Θ_3). Performance was assessed using DICE score and compared with an Otsu thresholded, vesselness filter[6] applied to the SWI and QSM images separately.

RESULTS:

Figure 1 presents a semi-transparent render of the SWI image from an example subject, overlaid with the various segmentations and ground-truth. Table 1 shows the DICE scores from the GMRF validation and the vesselness filter for each subject. The GMRF DICE score consistently outperforms the vesselness filter on both the SWI and QSM.

	μ (σ^2)
QSM	0.27 (0.03)
SWI	0.46 (0.02)
GMRF	0.52 (0.02)

Table 1: Average DICE score for vesselness on QSM, vesselness on SWI and GMRF.

DISCUSSION:

The combination of both contrasts, QSM and SWI, shows promising results that can partially be attributed to their complimentary nature. The smoothness and high surface signal-to-noise of SWI compliments the quantitative nature and high precision of QSM, whilst reducing some sources of error such as orientation dependence and surface noise. The use of GMM to combine the contrasts has inherent benefits, such as being unsupervised, and it provides a high contrast-to-noise dataset for the Gabor filter bank. Unlike traditional MRFs, the use of co-oriented cliques with Gabor filters overcomes the issue of mismatched species sizes, where the proportion of venous voxels to total brain voxels is quite small, whilst promoting a cylindrical structure.

CONCLUSION:

The GMRF method combines the voxel-based information from QSM and SWI, with local shape information, to segment the cerebral venous vasculature. Future work will be focused on improving the Gabor filter bank and cliques for multi-scale 3D cylindrical structures and testing it across a larger cohort of subjects.

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