Brain Artery Segmentation for Structural MRI

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Introduction

Neurological disorders are often linked to cerebrovascular diseases. If available, angiographic images like time-of-flight MR angiography (TOF) are preferred for the **assessment of brain arteries** due to their high contrast, and their automatic segmentation has been extensively studied. However, a comprehensive assessment also includes the **surrounding brain tissue**, which is better visualized in **structural MR images** (sMRI). Lee et al. [1] demonstrated that sMRI are suitable for the clinical assessment of brain arteries. Their **delineation remains challenging** due to the lack of vessel contrast, as illustrated in Figure 1. Verleger et al. [2] have indicated that using **masked vessels** for registration can significantly enhance the alignment of brain arteries. We aim to leverage this technique for aligning sMRI and TOF images to achieve **accurate image fusion**.

In our previous work [3] we demonstrated the **automatic segmentation** of large brain arteries around the Circle of Willis (CoW) in sMRI and annotated four circulatory regions. This approach had limitations: it relied on automatically **generated ground-truth** annotations, which were limited to **larger arteries.** Additionally, the **registration method** [4] required meticulous supervision to identify and correct poor alignments. We recently addressed the alignment problem with a **robust geometric registration** method [5] using annotated circulatory regions for accurate vessel alignments.

In this paper, we propose an automated strategy to overcome the limitations of our previous segmentation method. Our approach uses **pseudo labels** based on **gold-standard segmentations** of brain arteries and improves their **alignment with sMRI** through our **geometry-based registration** method. The process can be automatically applied to new data to retrain and enhance the model.

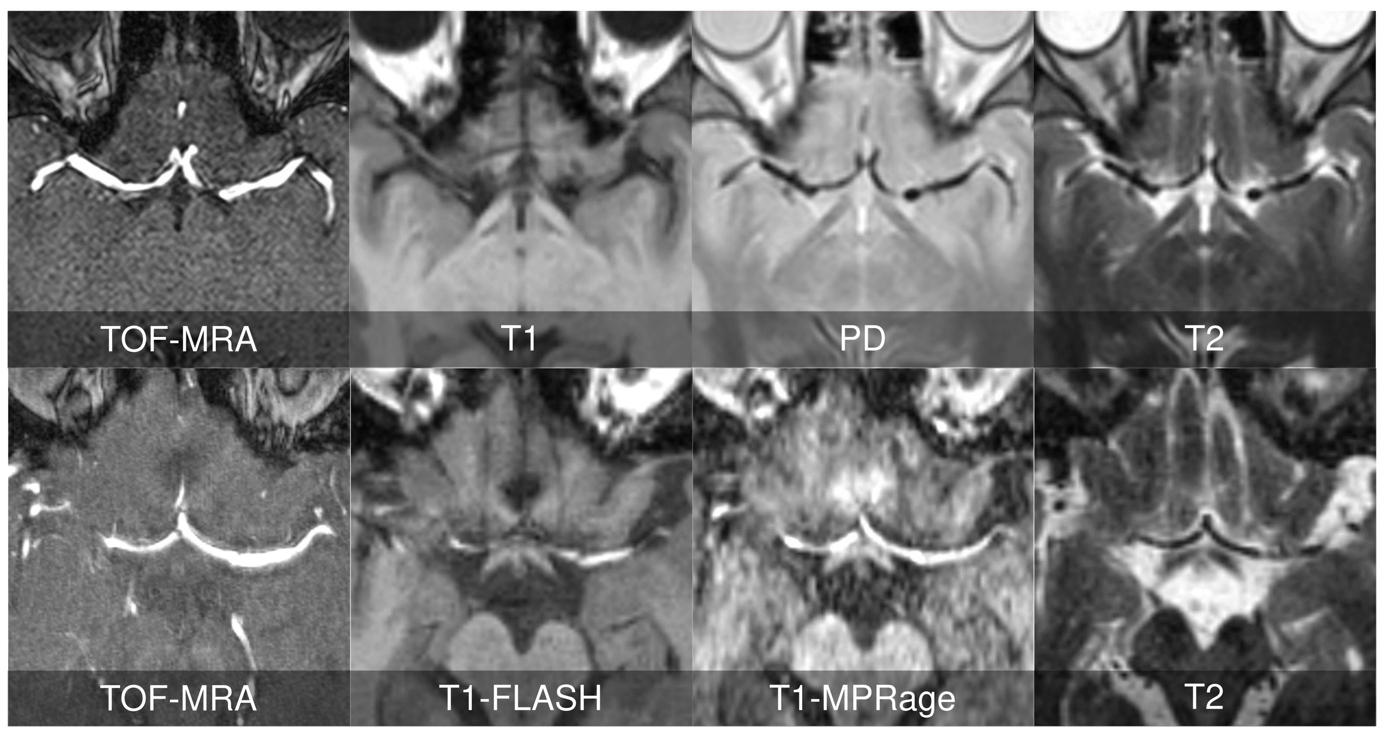

Figure 1: Discernibility of cerebral arteries across various MR sequences of an aligned patient dataset of IXI (top) and the TubeTK (bottom), respectively.

Methodology

Our study uses a large collection of 2,626 MR images of 699 patients from the **IXI** and **TubeTK** datasets. The data included **six sequences**: TOF, PD, T1, T2, T1-Flash and T1-MPRage. Our method comprises two distinct modules for **segmentation** and **registration** as outlined in Figure 2.

We trained an **nnU-Net** [6] model M_A on publicly available **gold-standard ground-truth** [7,8] for 87 of the TOF images, achieving a Dice Similarity Coefficient (DSC) of **0.82** in a 5-fold cross validation. The **segmentation module** uses this model to predicte **detailed pseudo labels** L for all TOF images.

The **registration module** utilizes our established model M_B [2] to annotate **major brain arteries** in TOF and sMRI images. It then employs our geometry-based registration method [4] to **align these annotations**, which allowed us to **warp and resample** the sMRI to match the TOF images.

In the final step, the TOF and the resampled $\overline{sMRI}$, along with the pseudo labels L, were used to train the **final model** M_C for **detailed segmentation** of brain arteries in **all available MR** sequences.

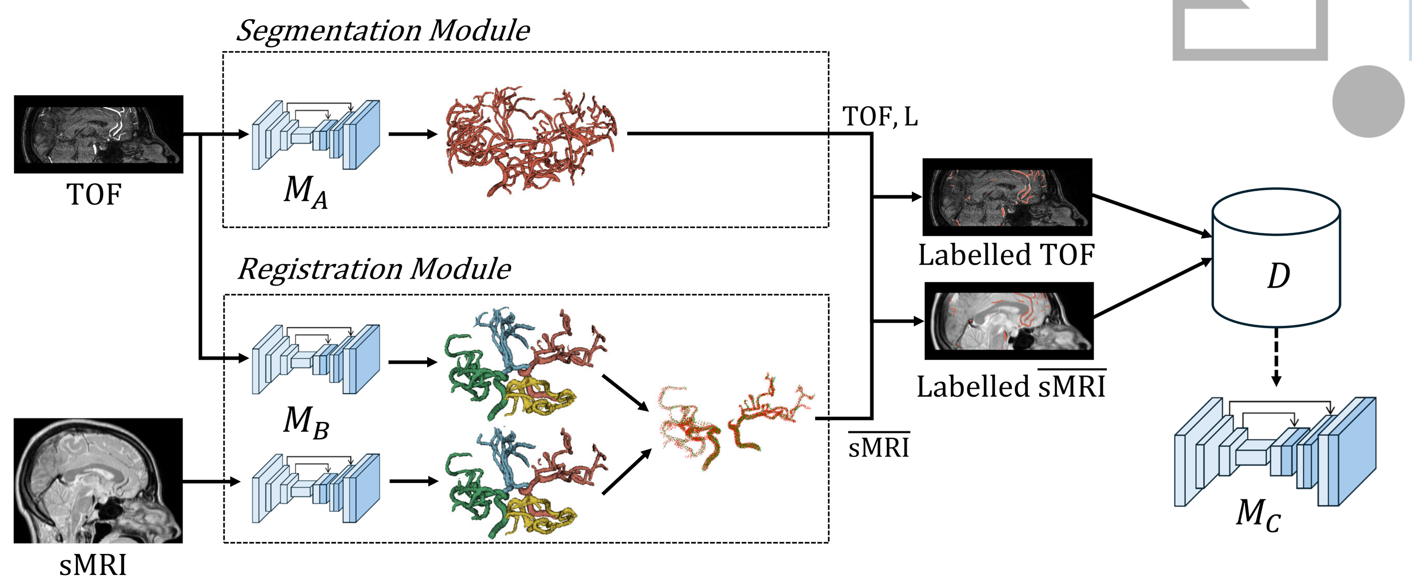

Figure 2: Overview of our method, which combines a segmentation and a registration module to generate data for the training of model M_C.

Results

We trained and evaluated model M_C in a 5-fold cross-validation. The DSC metric was assessed in both the **full image** region and a smaller region **around the CoW**. Our model achieved an average DSC of **0.66** across **all sMRI** around the CoW. The results for each MR sequence are detailed in Table 1 and Figure 3. The model accurately detected **larger vessels** across **all sMRI** sequences, although **small arteries** were significantly **undersegmented**, particularly outside the CoW region. This observation can be partially explained by the generally **lower resolution** of the sMRI, which inhibits the detectability of smaller vessels. Out of the sMRI, the **PD** sequence yielded the best results followed by **T2**.

Table 1: DSC scores for each dataset and both, the full image and CoW region.

Region	Dataset	TOF	PD	T1	T2	MPR	FL
Full	All	0.91±0.06	**0.57±0.06**	0.49±0.05	0.53±0.06	0.46±0.06	0.40±0.05
	Guys	0.93±0.01	0.59±0.05	0.49±0.05	0.55±0.05	-	-
	HH	0.94±0.01	0.56±0.06	0.52±0.04	0.51±0.06	-	-
	IOP	0.86±0.04	0.55±0.04	0.43±0.04	0.53±0.05	-	-
	TTK	0.82±0.08	-	-	0.48±0.06	0.46±0.06	0.40±0.05
CoW	All	0.94±0.04	**0.70±0.06**	0.64±0.06	0.67±0.07	0.61±0.08	0.58±0.06
	Guys	0.95±0.01	0.71±0.07	0.64±0.07	0.69±0.07	-	-
	HH	0.96±0.01	0.69±0.06	0.67±0.04	0.66±0.06	-	-
	IOP	0.91±0.02	0.70±0.04	0.61±0.05	0.68±0.04	-	-
	TTK	0.87±0.07	-	-	0.60±0.07	0.61±0.08	0.58±0.06

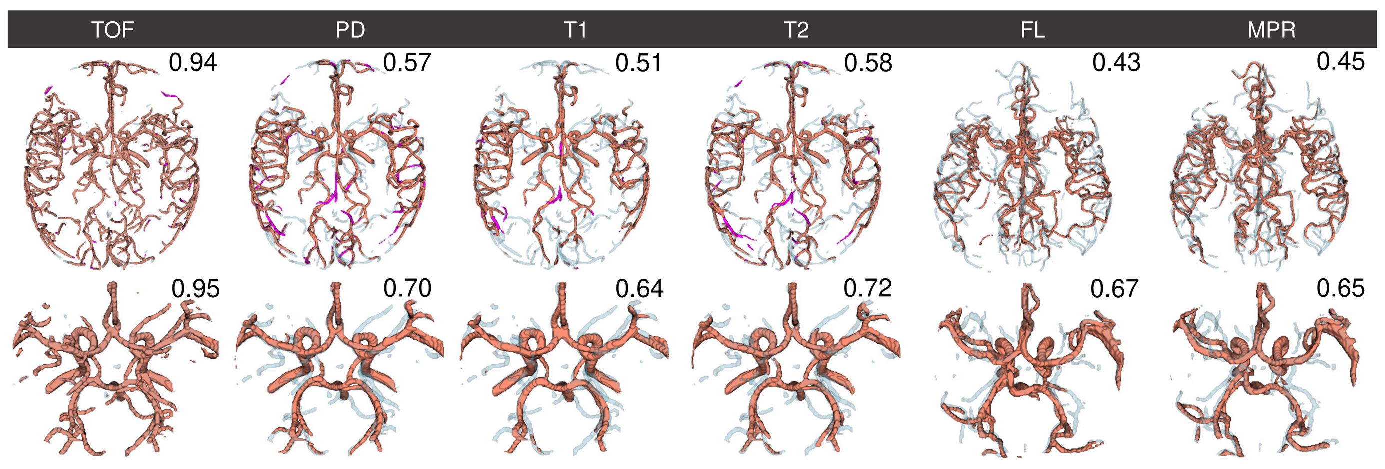

Figure 3: Visualizations and DSC scores for the full (top) and CoW region (bottom) of examples for each MR sequence. Oversegmentation is shown in magenta and undersegmented ground-truth in light-blue.

Conclusion

We proposed a novel method for the segmentation of brain arteries in sMRI, which extends our previous work on the topic. While our method achieved significantly better results for the angiographic TOF sequence, we also obtained good results for sMRI, particularly for the **PD sequence** and the **CoW region**. Our method is not intended to replace angiographic images but to complement them by **delineating vessels** in sMRI. This offers a common reference for vessel **assessment** and can facilitate precise vessel **alignment** for accurate image fusion. Using our method, new data can be automatically processed to extend the training dataset and **further improve** the model. In our next steps we plan to refine the alignment of arteries through a non-linear registration step, using masks of vessels obtained with this method.

Details on our methods as well as an upcoming in-depth publication are shared at our repository: `github.com/risc-mi/cerebral-artery-segmentation`.

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Acknowledgments: This work was funded by the FFG (Austrian Research Promotion Agency) under the grant 872604 (MEDUSA) and research subsidies granted by the government of Upper Austria.
RISC Software GmbH is a member of UAR (Upper Austrian Research) Innovation Network.

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