# A Multi-View Approach for Automatic Segmentation of Intracranial Aneurysms from Time of Flight MRAs

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## 1 Motivation

The detection of intracranial aneurysms from time of fight (TOF) MRAs strongly relies on global anatomical knowledge of the brain. Ideally a 3D approach would be helpful to capture spatial information but it is computationally expensive and is constrained by the limited number of training samples. Furthermore, as a region of interest, the tiny structure of intracranial aneurysms naturally pose a challenge for the imbalanced binary segmentation problem. Thus we hypothesize that the image features from the different geometric views would be complementary to locate the intracranial aneurysms and would be beneficial for reducing false positives on individual views. To this end, we solve the segmentation task using a 2D but multi-view approach considering the computation complexity and multi-view anatomical knowledge.

## 2 Method

**Pre-processing.** We parse the 3D volumes into different views: axial, sagittal and coronal. We found axial view is not helpful for detecting the lesion, thus it is excluded during the training stage. We perform *z-score* normalization on each slice before feeding them to the model. We further exclude top 20% and bottom 20% slices where the lesion are probably not presented. We crop or pad the slices to a uniform size of $448 \times 140 \times 2$ after concatenating both structural and TOF imaging data into two channels.

**Single-View Convolutional Neural Netowork.** For each view, a U-Net [2] based architecture was employed to segment the lesions using the MOF and structural data. Please refer to [1] for the details of the network.

**Multi-View Ensemble.** We propose a simple approach to aggregate the multi-view information in the probability space in voxel-wise level during the testing

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stage. Let $f_s$(x) and $f_c$(x) be the single-view models trained on the 2D image slices from saggital and coronal views respectively. During the testing stage, given an image volume (scan) $V \in \mathbb{R}^{d_1,d_2,d_3}$, it is transposed to the sagittal space and coronal space $V_s \in \mathbb{R}^{w_s,h_s,n_s}$ and $V_c \in \mathbb{R}^{w_c,h_c,n_c}$ by function $T_s$ and $T_c$ respectively, where $w_s$, $w_c$, $n_s$ ,$n_c$ and $h_s$, $h_c$ are the widths, heights and number of the sagittal and coronal slices respectively. Let $P_s$ and $P_c$ be the segmentation maps in volumes predicted by $f_s$(x) and $f_c$(x) respectively. We fuse the multi-view information by averaging the voxel-wise probabilities generated by single-view models. The final segmentation masks in volume after ensemble is define as:

$$P_F = \frac{1}{2}(\lambda T_s^{-1}(P_s) + (1 - \lambda)T_c^{-1}(P_c)) \tag{1}$$

where $T_s^{-1}$ and $T_c^{-1}$ are the inverse sagittal-transformation functions of $T_a$ and $T_c$ respectively. $\lambda$ is used to balance the contribution of each view and it is set to 0.5 in the experiments.

**Data Augmentation.** We perform data augmentation on the fly, including rotation, shearing and flipping.

**Post-processing.** We perform 3D connected component analysis to remove the potential false positives with a volume less than 5.

## References

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