Segmentation of Intracranial Aneurysm Remnant in MRA using Dual-Attention Atrous Net

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Introduction

- An intracranial aneurysm (IA) is a swelling of an artery [1]. Typically treated by endovascular coiling.
- Time-of-Flight Magnetic Resonance Angiography (ToF MRA) images are used for detection and diagnosis [2].
- Accurate quantification of the IA and IA remnants (IARs) are important, which is typically done manually [3, 4].
- Manual segmentation of volumetric images is a labour-intensive and error-prone process.
Objective

- Segmentation of IAR is very challenging
  - small and irregular shape
  - indistinguishable nature from the surrounding vessels
- Adjusting parameters for acceptable segmentation of IARs in different database is a limitation of existing approaches.
- Generic CNNs based segmentation models are not capable of handling issues involved in small, irregular object segmentation.
Contribution

- We proposed a novel CNN called Dual-Attention Atrous Net (DAtt-ANet) for volumetric segmentation of IAR from MRA images.
- We replaced the normal contraction blocks in the U-Net with proposed Parallel Atrous Unit (PAU), to help the encoder extract of the predominant vascular structure.
- We used two parallel attention blocks
  - “spatial-attention” – to focus on the most informative region
  - “channel-attention” – to find out which feature map is important by calculating interchannel relationship
Dataset

- A clinical MRA image database (UU-IAR-V1) was collected from the Uppsala University hospital.
- Contains 46 MRA image volumes.
- Each MRA volume consists of 150 2D slices of 512X512 resolution.
- Generation of ground truths (GT) was done by an expert radiologist from Uppsala University hospital.
Dual-Attention Atrous Net (DAtt-ANet)
Parallel Atrous Unit (PAU)

Parallel Atrous Unit [PAU(N, F, d₀, S)]

3X3 Atrous Conv. + ReLU
(Number of atrous units, F = Number of convolution filters, DR = Dilation rate, S = stride)

Sample MRA patch

Ground truth

DR = 1
DR = 3
DR = 5

Fig. 3. Parallel Atrous Unit (PAU).

Fig. 5. Localization of IAR using PAU for a sample MRA patch.
Spatial and channel attentions

\[
S_{j,i} = \frac{\exp((A')^T_i \cdot B_j)}{\sum_{i=1}^{N} \exp((A')^T_i \cdot B_j)}.
\]
Experimental setup

- Patch-based training and testing - vessel centerline based volumetric patch extraction.
- 5-fold cross-validation strategy was used.
- The segmentation accuracy was measured w.r.t. ground truth in terms of (i) Dice score, (ii) volumetric similarity, and (iii) Hausdorff Distance [14].
- Adam optimization algorithm was used for parameter optimization.
- Real-time data augmentation was used to artificially enhance the number of training samples.
Comparison with state-of-the-art

Fig. 7. Box plots of segmentation performance of the proposed DA2t-ANet along with U-Net, R-U-Net, Att-U-Net, P-Net and ResInc-Net measured by Dice score, volumetric similarity and Hausdorff distance in a 5-fold cross validation setting.
Comparison with state-of-the-art

**TABLE I**


<table>
<thead>
<tr>
<th>Models (#parameters)</th>
<th>DICE</th>
<th>VS</th>
<th>HD</th>
</tr>
</thead>
<tbody>
<tr>
<td>DAtt-ANet (654, 217)</td>
<td>0.73 ± 0.06</td>
<td>0.84 ± 0.09</td>
<td>04.62 ± 2.79</td>
</tr>
<tr>
<td>U-Net (925, 297)</td>
<td>0.48 ± 0.20</td>
<td>0.65 ± 0.19</td>
<td>39.19 ± 27.01</td>
</tr>
<tr>
<td>R-U-Net (1, 139, 057)</td>
<td>0.51 ± 0.17</td>
<td>0.67 ± 0.17</td>
<td>38.22 ± 23.26</td>
</tr>
<tr>
<td>Att-U-Net (941, 761)</td>
<td>0.61 ± 0.09</td>
<td>0.74 ± 0.11</td>
<td>13.52 ± 10.31</td>
</tr>
<tr>
<td>P-Net (1, 339, 189)</td>
<td>0.56 ± 0.11</td>
<td>0.67 ± 0.12</td>
<td>24.02 ± 19.95</td>
</tr>
<tr>
<td>ResInc-Net (3, 276, 628)</td>
<td>0.54 ± 0.08</td>
<td>0.62 ± 0.09</td>
<td>25.75 ± 11.95</td>
</tr>
</tbody>
</table>
Ablation studies

<table>
<thead>
<tr>
<th>Effect of patch size</th>
<th>Without augmentation</th>
<th>Without attention</th>
</tr>
</thead>
<tbody>
<tr>
<td>32 × 32</td>
<td>Train</td>
<td>No channel-attention</td>
</tr>
<tr>
<td>0.42 ± 0.25</td>
<td>0.83 ± 0.08</td>
<td>0.60 ± 0.12</td>
</tr>
<tr>
<td>64 × 64</td>
<td></td>
<td>No spatial-attention</td>
</tr>
<tr>
<td>0.73 ± 0.05</td>
<td>0.52 ± 0.15</td>
<td>0.63 ± 0.24</td>
</tr>
<tr>
<td>96 × 96</td>
<td></td>
<td>Without both</td>
</tr>
<tr>
<td>0.68 ± 0.08</td>
<td></td>
<td>0.51 ± 0.36</td>
</tr>
</tbody>
</table>
Conclusion

- An MRA image dataset was collected and annotated.
- A novel CNN architecture called DAtt-ANet for automated segmentation of IAR volumes was developed.
- The concepts of attention guided localization was efficiently implemented by aggregating multi-resolution feature maps using atrous convolutions.
- The proposed DAtt-ANet performed satisfactorily and outperformed state-of-the-art models.
- We are still collecting and annotating IAR cases and planning to release a larger dataset in the future.
References


References


References


