

Attention via Scattering Transforms for Segmentation of Small Intravascular Ultrasound Data Sets

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Motivation

- Limited data for CNN training leads to inefficient filters unable to extract meaningful features.
- The scattering transformation, basically a special form of CNN with pre-defined filters, is able to produce meaningful features without learning weights.
- Combining CNNs with scattering transformations could improve segmentation performance when dealing with small amounts of data.
- We investigate this hypothesis using segmentation of intravascular ultrasound images.

Methods

- An ordinary wavelet transformation can be calculated by applying a filter cascade with low-pass filters ϕ and band-pass filters ψ (Fig. 1).
- Scattering transformations also rely on a wavelet basis, but band-pass filters are applied to all intermediate feature maps (Fig. 2).
- Problem: exponential growth of output feature maps with increasing order of transformation.
- Solution: use scattering transformation in a squeeze and excitation block (SEST) (Fig. 3).

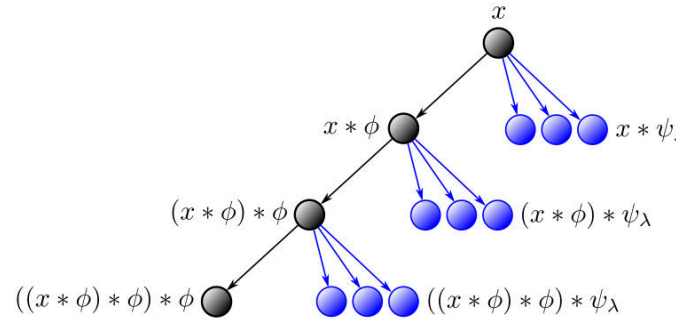


Fig. 1: Diagram of a wavelet transformation

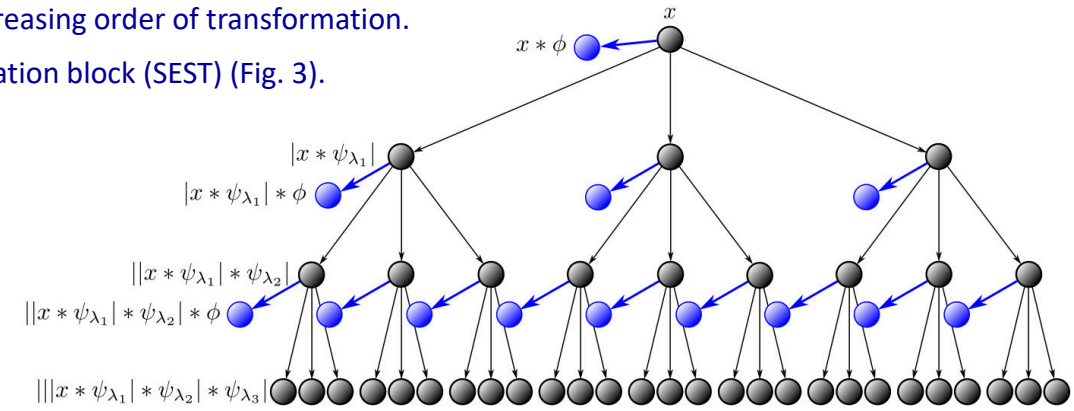


Fig. 2: Diagram of a scattering transformation

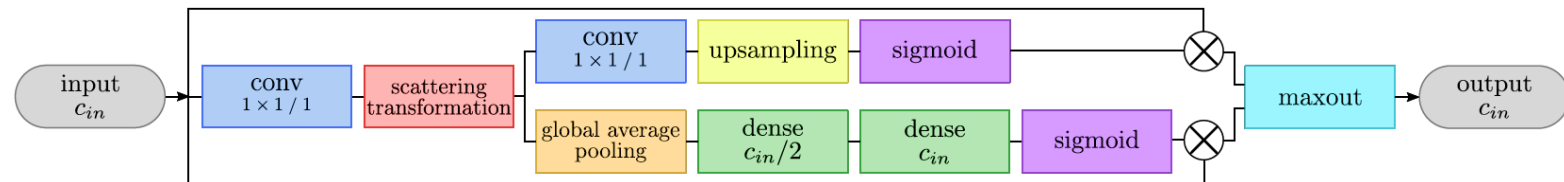
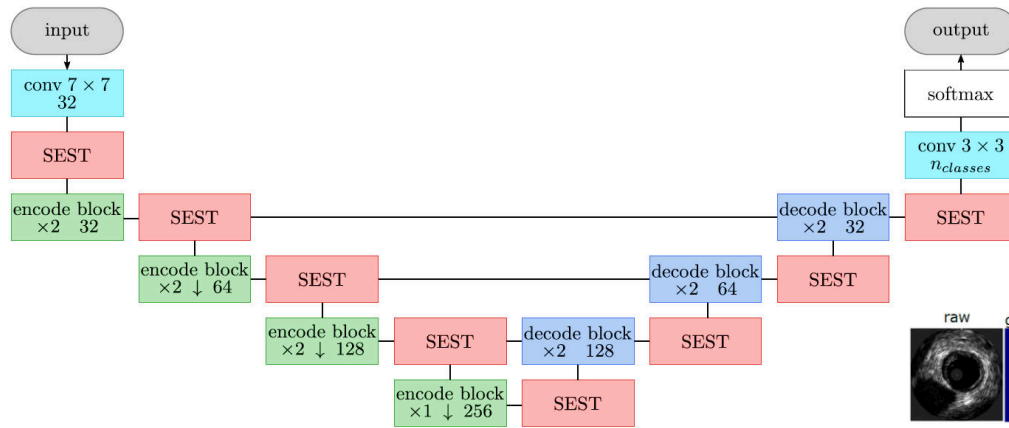


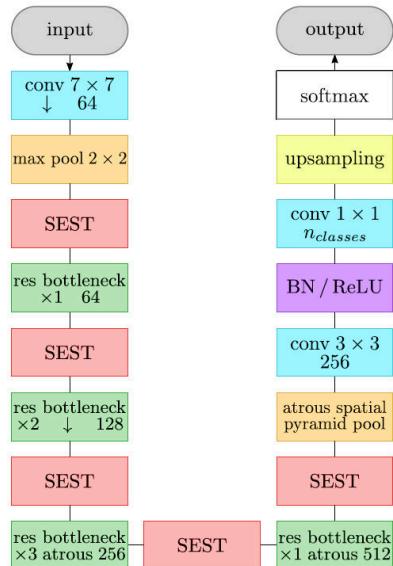
Fig. 3: Diagram of the proposed squeeze and excitation block with scattering transformation (SEST) block

CNN Architectures

U-Net Res SEST



DeepLabV3 SEST



Data sets

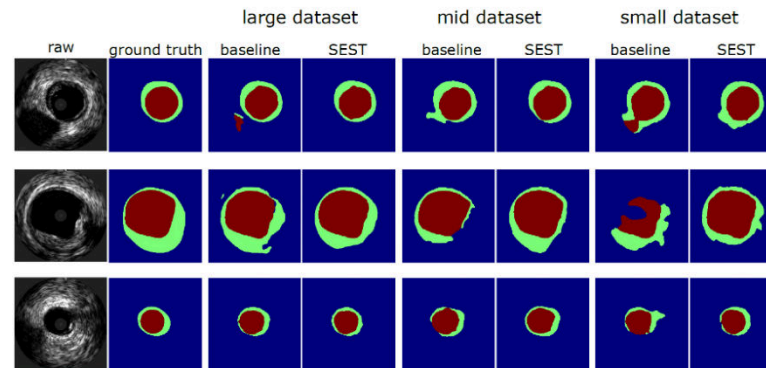
Calcium segmentation

- training images
 - large: 318
 - mid: 145
 - small: 90
- test images: 114

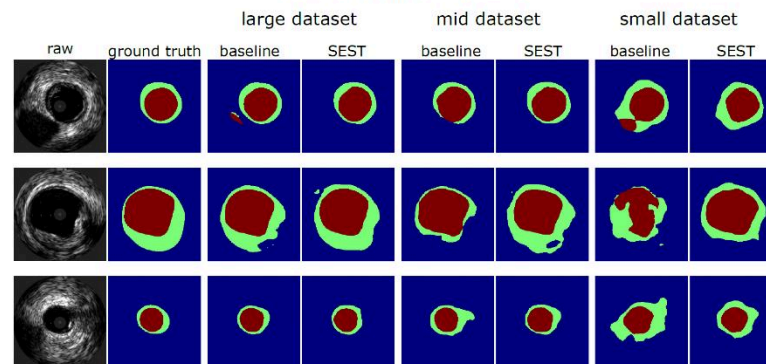
Lumen/vessel wall segmentation

- training images
 - large: 289
 - mid: 146
 - small: 73
- test images: 121

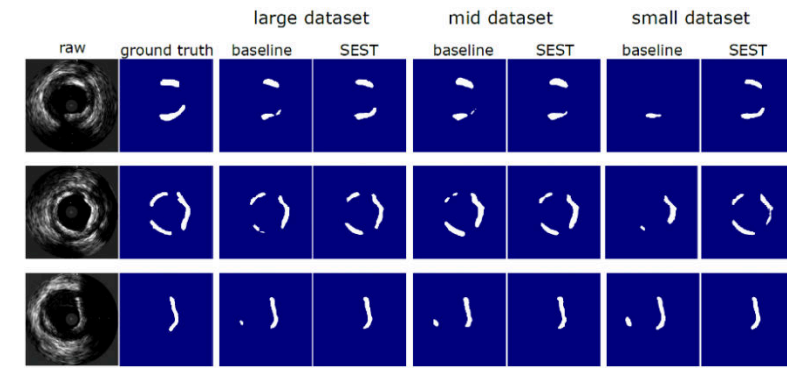
Lumen/Wall: U-Net Res



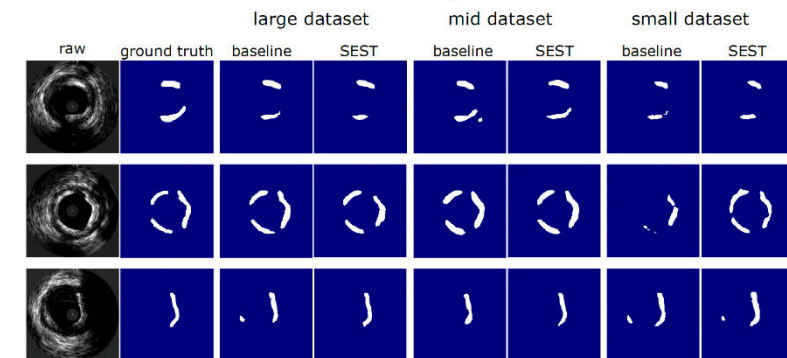
Lumen/Wall: DeepLabV3



Calcium: U-Net Res



Calcium: DeepLabV3



Results and Discussion

- Calcium segmentation (Tab. 1): improvements by SEST are statistically significant for all data set sizes.
- Improvements are larger on smaller data sets.
- Largest improvements are 6% (relative) for the Dice coefficient and 21% for the average Hausdorff distance.
- Vessel wall (Tab. 2) and lumen (Tab. 3) segmentation: improvements by SEST are almost only statistically significant for the smallest data sets.
- On small data sets, U-Net Res produces better results for vessel wall and lumen segmentation compared to DeepLabV3.

Tab. 2: Results of vessel wall segmentation.

| model | dset size | method | Dice coefficient [%] | | ave. Hausd. dist. [px] | |
|-----------|-----------|----------|----------------------|---------|------------------------|---------|
| | | | value | p-value | value | p-value |
| U-Net Res | large | wavelet | 79.51 \pm 0.57 | 0.14 | 1.85 \pm 0.10 | < 0.01 |
| | | baseline | 79.29 \pm 0.50 | | 2.03 \pm 0.11 | |
| | mid | wavelet | 76.15 \pm 0.61 | 0.08 | 2.56 \pm 0.18 | 0.02 |
| | | baseline | 75.86 \pm 0.47 | | 2.69 \pm 0.15 | |
| | small | wavelet | 67.05 \pm 1.23 | 0.19 | 4.80 \pm 0.44 | < 0.01 |
| | | baseline | 66.63 \pm 1.39 | | 5.36 \pm 0.43 | |
| DeepLabV3 | large | wavelet | 77.86 \pm 0.52 | 0.33 | 2.16 \pm 0.14 | 0.31 |
| | | baseline | 77.78 \pm 0.49 | | 2.18 \pm 0.08 | |
| | mid | wavelet | 74.44 \pm 0.58 | < 0.01 | 2.69 \pm 0.16 | 0.03 |
| | | baseline | 73.79 \pm 0.72 | | 2.85 \pm 0.27 | |
| | small | wavelet | 62.20 \pm 1.30 | < 0.01 | 5.07 \pm 0.25 | < 0.01 |
| | | baseline | 60.91 \pm 1.37 | | 5.80 \pm 0.48 | |

Tab. 1: Results of calcium segmentation.

| model | dset size | method | Dice coefficient [%] | | ave. Hausd. dist. [px] | |
|-----------|-----------|----------|----------------------|---------|------------------------|---------|
| | | | value | p-value | value | p-value |
| U-Net Res | large | wavelet | 66.94 \pm 0.48 | < 0.01 | 7.92 \pm 0.60 | < 0.01 |
| | | baseline | 66.20 \pm 0.90 | | 8.89 \pm 1.12 | |
| | mid | wavelet | 64.74 \pm 0.69 | < 0.01 | 10.32 \pm 1.06 | < 0.01 |
| | | baseline | 63.69 \pm 0.96 | | 11.96 \pm 1.29 | |
| | small | wavelet | 58.62 \pm 1.46 | < 0.01 | 13.31 \pm 1.20 | < 0.01 |
| | | baseline | 55.38 \pm 2.99 | | 16.89 \pm 3.45 | |
| DeepLabV3 | large | wavelet | 66.57 \pm 0.34 | < 0.01 | 8.09 \pm 0.48 | < 0.01 |
| | | baseline | 66.00 \pm 0.42 | | 8.61 \pm 0.50 | |
| | mid | wavelet | 62.36 \pm 0.43 | < 0.01 | 11.83 \pm 0.68 | < 0.01 |
| | | baseline | 61.38 \pm 0.77 | | 12.93 \pm 0.94 | |
| | small | wavelet | 59.71 \pm 0.95 | < 0.01 | 11.51 \pm 0.88 | < 0.01 |
| | | baseline | 55.18 \pm 3.86 | | 15.30 \pm 4.56 | |

Tab. 3: Results of lumen segmentation.

| model | dset size | method | Dice coefficient [%] | | ave. Hausd. dist. [px] | |
|-----------|-----------|----------|----------------------|---------|------------------------|---------|
| | | | value | p-value | value | p-value |
| U-Net Res | large | wavelet | 90.54 \pm 0.36 | 0.39 | 1.40 \pm 0.17 | 0.05 |
| | | baseline | 90.50 \pm 0.34 | | 1.51 \pm 0.17 | |
| | mid | wavelet | 90.12 \pm 0.60 | 0.68 | 1.38 \pm 0.19 | 0.09 |
| | | baseline | 90.22 \pm 0.49 | | 1.53 \pm 0.39 | |
| | small | wavelet | 86.59 \pm 1.07 | < 0.01 | 2.94 \pm 0.97 | < 0.01 |
| | | baseline | 84.63 \pm 0.58 | | 4.25 \pm 0.56 | |
| DeepLabV3 | large | wavelet | 90.12 \pm 0.41 | 0.07 | 2.16 \pm 0.14 | 0.07 |
| | | baseline | 89.93 \pm 0.26 | | 1.57 \pm 0.13 | |
| | mid | wavelet | 89.81 \pm 0.41 | 0.01 | 1.40 \pm 0.20 | 0.06 |
| | | baseline | 89.44 \pm 0.46 | | 1.58 \pm 0.38 | |
| | small | wavelet | 84.61 \pm 1.06 | < 0.01 | 3.05 \pm 0.83 | < 0.01 |
| | | baseline | 83.51 \pm 0.83 | | 3.96 \pm 0.86 | |

Conclusion

- Inserting scattering transformations into CNNs via an attention mechanism (SEST) improves segmentation results on small intravascular ultrasound datasets.
- We can therefore conclude that the features extracted by the scattering transformations inside the SEST blocks provide meaningful information.
- The approach works better for segmentation of small structures like calcifications.
- The attention approach with SEST seems to be less effective for larger structures like lumen or vessel wall.
- SEST can be flexibly inserted into any CNN.

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