Attention for Damage Assessment

Tashnim Chowdhury, Maryam Rahnemoonfar

Computer Vision and Remote Sensing Lab (Bina Lab),

Department of Information Systems,

University of Maryland Baltimore County

UMBC

Bina

Computer Vision and Remote Sensing Lab

Agenda

- Motivation
- Data Collection and Annotation
- Semantic Segmentation Method
- Experimental Results
- Conclusion

Motivation

- Recently natural disaster have caused both human lives and economic losses [1].
- An accurate assessment helps to make rescue plans efficiently.
- Unmanned Aerial Vehicle (UAV) can access difficult places and provides better resolution images.
- DCNN (Deep Convolutional Neural Network) have achieved remarkable performance in assessing damages.
- Research works lack complete image understanding to evaluate the disaster damage scenario completely.

Dataset Collection and Annotation

- Resolution of the captured images are 3000 x 4000.
- The FloodNet [2] dataset consists of video and imagery taken from 80 flights conducted between August 30 – September 04, 2017 after hurricane Harvey.
- All flights were flown at 200 feet AGL, as compared to manned assets which normally fly at 500 feet AGL or higher.
- For quality assurance of the annotation, each image passes through two steps verification process.
- All Classes: Building Flooded, Building Non Flooded, Road Flooded, Road Non Flooded, Water, Tree, Vehicle, Pool, and Grass.

Data Annotation Example

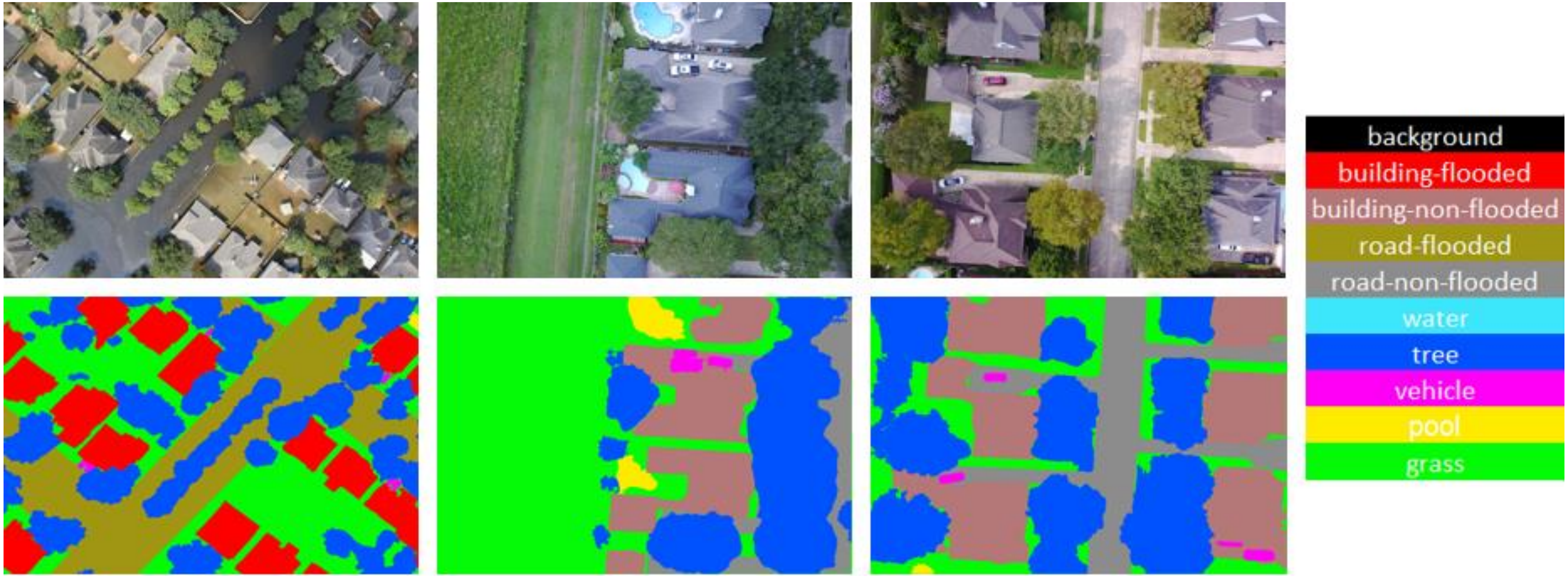

Figure: Sample images from FloodNet.

Semantic Segmentation Method: ReDNetPlus

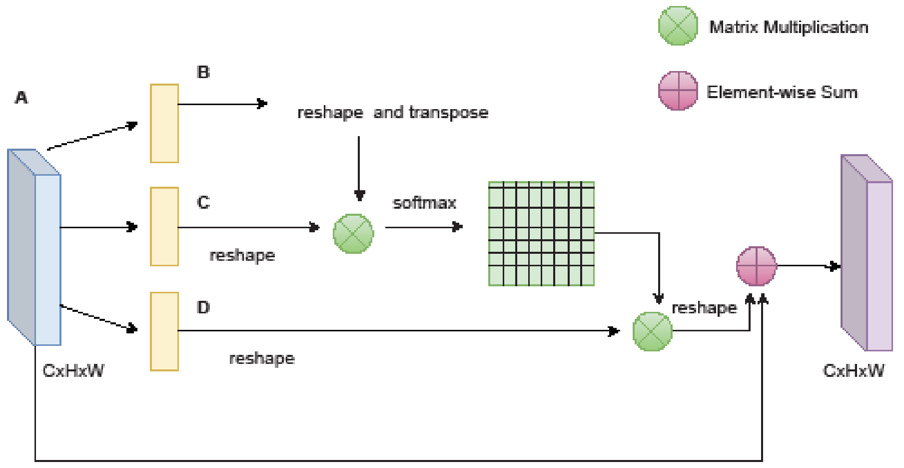

Figure : Position Attention Module (PAM).

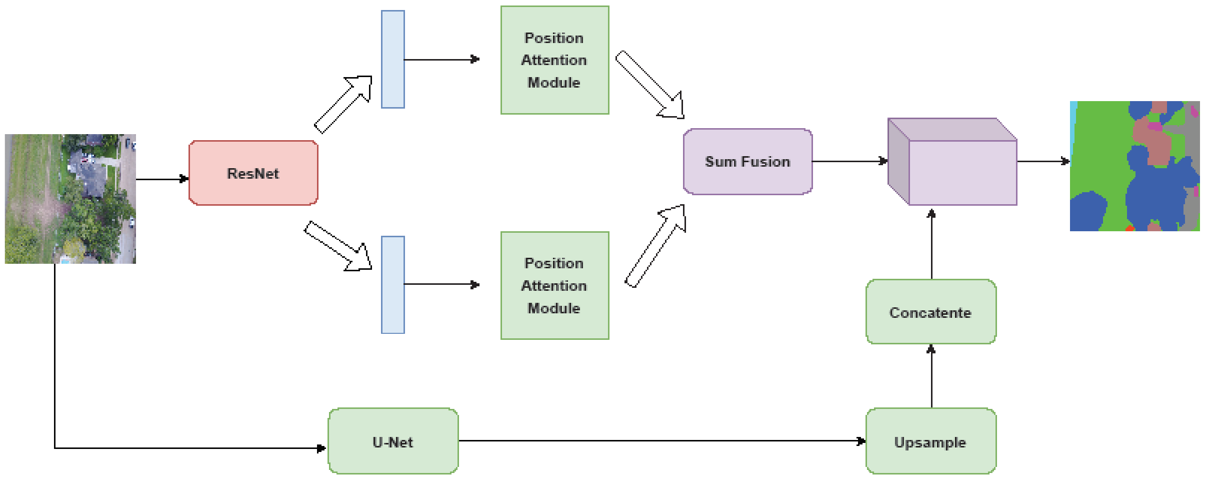

Figure : Overview of ReDNetPlus architecture.

Experimental Result

Table: Per-class segmentation results on FloodNet test set.

Method	Building Flooded	Building Non Flooded	Road Flooded	Road Non Flooded	Water	Tree	Vehicle	Pool	Grass	MIoU
ENet [3]	21.82	41.41	14.76	52.53	47.14	62.56	26.21	16.57	75.57	39.84
DeepLabv3+ [4]	28.10	78.10	32.00	81.10	73.00	74.50	33.60	40.00	87.10	58.61
PSPNet [5]	65.61	90.92	78.69	90.90	91.25	89.17	54.83	66.37	95.45	80.35
Attention U-Net [6]	64.82	86.14	28.20	92.35	77.74	90.95	54.20	71.82	95.29	73.50
ReDNetPlus	80.99	91.76	88.90	91.90	95.56	91.20	48.68	70.90	96.39	84.03

Experimental Result

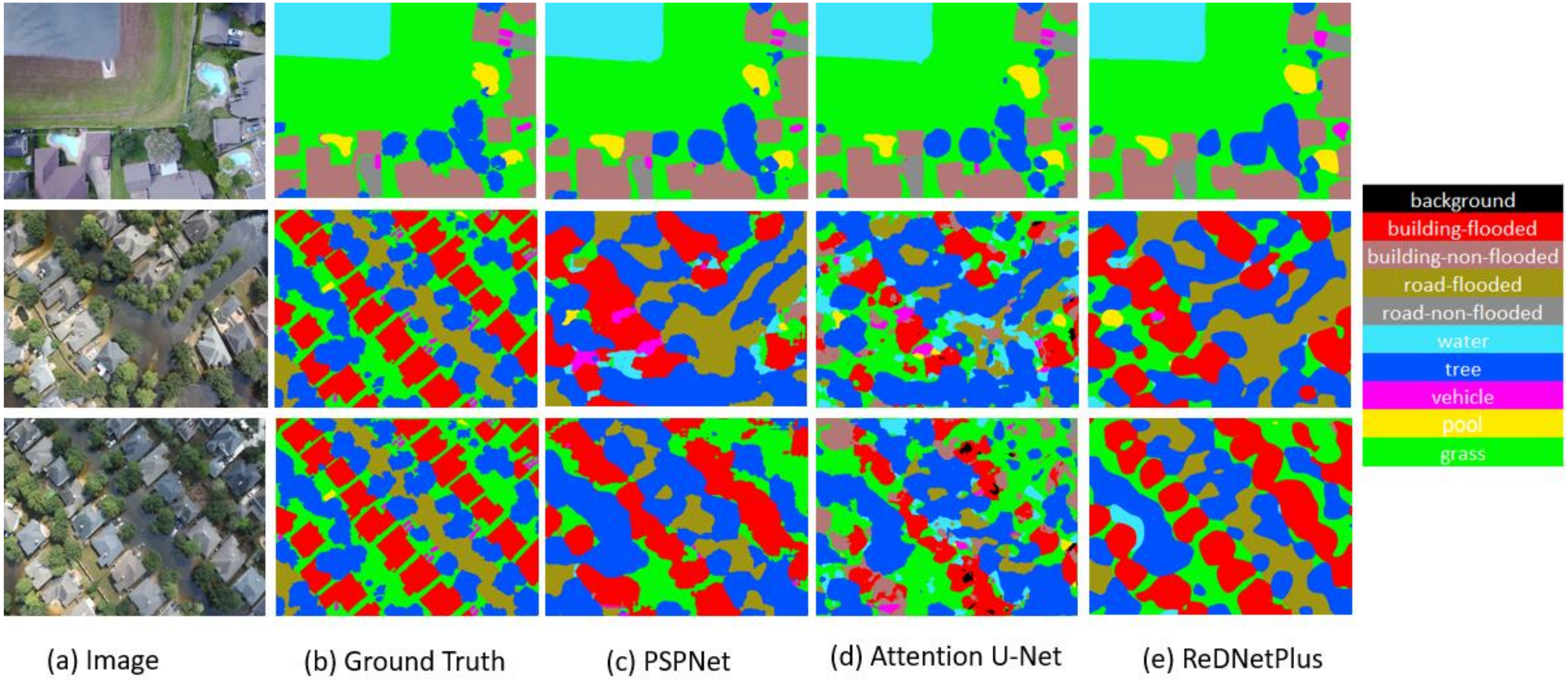

Figure: Visualization of Segmentation of all classes on FloodNet test set.

Conclusion

- An attention based semantic segmentation method, ReDNetPlus, has been implemented on a new high resolution natural disaster dataset named FloodNet.
- Performance of the proposed method has been compared with four popular state-of-art semantic segmentation models.
- ReDNetPlus performed best among all the methods implemented.
- New attention-based methods can be explored in future.

References

1. “Noaa national centers for environmental information (ncei). u.s. billion-dollar weather and climate disasters.” https://www.ncdc.noaa. gov/billions/events. Accessed: 2021-07-09.
2. Rahnemoonfar, M., Chowdhury, T., Sarkar, A., Varshney,D., Yari, M., and Murphy, R. Floodnet: A high resolutionaerial imagery dataset for post flood scene understanding. IEEE Access, 2021.
3. A. Paszke, A. Chaurasia, S. Kim, and E. Culurciello, “Enet: A deep neural network architecture for real-time semantic segmentation,” arXiv preprint arXiv:1606.02147, 2016.
4. L.-C. Chen, Y. Zhu, G. Papandreou, F. Schroff, and H. Adam, “Encoderdecoder with atrous separable convolution for semantic image segmentation,” in Proceedings of the European conference on computer vision (ECCV), pp. 801–818, 2018.
5. H. Zhao, J. Shi, X. Qi, X. Wang, and J. Jia, “Pyramid scene parsing network,” in Proceedings of the IEEE conference on computer vision and pattern recognition, pp. 2881–2890, 2017.
6. Oktay, O., Schlemper, J., Folgoc, L. L., Lee, M., Heinrich,M., Misawa, K., Mori, K., McDonagh, S., Hammerla,N. Y., Kainz, B., et al. Attention u-net: Learning where tolook for the pancreas.arXiv preprint arXiv:1804.03999, 2018.

Acknowledgement

Microsoft

amazon