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Physics-Aware Deep Edge Detection Network

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ABSTRACT

In this paper, we describe an effort to build a new deep edge detection method designed to detect weather-related phenomena such as clouds and planetary boundary layer heights present in backscatter profile imagery. This method builds on the existing deep model called Holistically-Defined Edge Detection (HED), which was shown to perform better than other information theory and convolutional network techniques for edge detection. Though HED outperforms techniques such as Canny Edge detection, HED's performance is based on it being trained on natural images with very little noise. Weather-related backscatter profiles, such as those generated from LIDAR-based ceilometers, often contain noise. In addition, there is often less of a difference in the pixel density between edges and non-edges, and due to atmospheric dynamics, continuous edges are not always detected in the images. Under these conditions when using HED, subtle but useful edges are lost from side outputs during the fusing process while the network is being trained. Canny Edge detection also does not perform well under these conditions, as it determines edges based on the differences in pixel density. We describe a new edge detection deep network developed specifically for overcoming these issues by applying physics-aware attention mechanisms to the side outputs of the HED learning process. We show how this method is able to learn the subtle edges as opposed to HED or Canny, when used to identify planetary boundary layer heights which involves distinguishing the mixing layer, residual layer, and nocturnal layer in addition to the cloud heights for ceilometer-based backscatter. Though the intent of this network is to learn planetary boundary layer heights and cloud heights, this method could be applied to other weather-related phenomena and applied to backscatter imagery generated from other sources such as satellites.

1. INTRODUCTION

The planetary boundary layer (PBL), which is the lowest portion of the atmosphere, is vital for air quality assessments, where characterizing the vertical extent of boundary layer mixing is obtained by measuring the height.[1] The Weather Research and Forecasting models online coupled with a Chemistry package (WRF-Chem)[2] is one such model which is used to calculate PBLH. Though at current model resolution, calculating PBLH is not prohibitive, as model resolution increases, methods which support a reduction in computation will be advantageous. In addition, data assimilation models, such as WRF-Chem, under certain conditions will not accurately calculate PBLH.[3,4] For these reasons, there has been an exploration in using other methods for calculating PBLH. One such effort includes using ground-based LIDAR to augment data assimilated PBLH forecasts.[5] More recently, there have been efforts in using machine learning to identify[6] and forecast[7,8] PBLH both from ceilometers and from historical model data.

Our previous work[6] applied a pretrained edge detection network to LIDAR backscatter profiles to automatically estimate the PBLH for the mixing layer. Training the edge detection network specifically on the backscatter profiles is not possible as there is limited labeled data for training, and deep learning methods requires large training data sets in order to generalize well.[9] However, transfer learning[10] can be used under these conditions, using a model that is trained on a large dataset from a different origin and transferring the knowledge to a specific problem with a smaller dataset. In the case of edge detection, this is a reasonable approach. Though the work showed promise it was evident from the edge detected imagery that certain areas of the PBL that are more subtle, such as the residual layer, were harder to detect, as can be seen in Figure 1, where we show an example of a 24-hour backscatter profile, the result of applying edges detection using HED, and a super-resolved image highlighting the PBL. As can be seen from the super-resolved image, many of the details of the PBL layering are lost in the edge detection.

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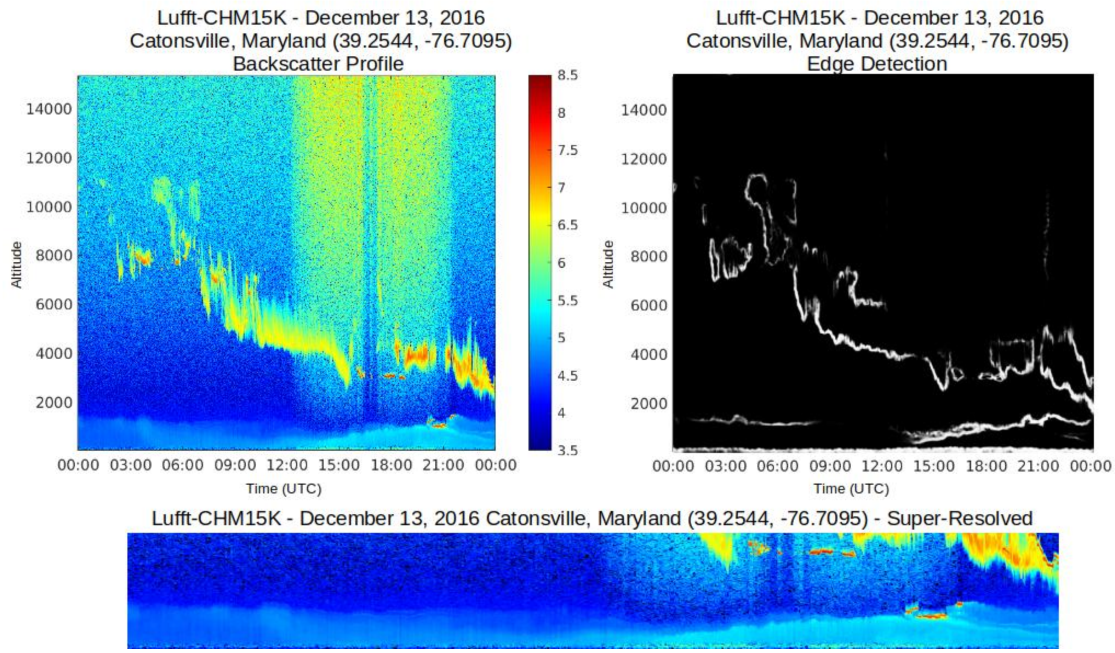

Figure 1. Lufft-CHM15K - Catonsville, MD - 24 Hour LIDAR Backscatter Profile, Edge Detected, and Super-Resolved - 12/13/2016.

In this work we describe a method supplemental to HED[11] edge detection that enables more "physic-aware" learning by first identifying the area of the backscatter which is estimated to be the region of the PBL and using that knowledge during training to enhance the part of the image for edge detection where the PBL is located. We train the HED[11] network to give attention to the details of this region of the imagery, enabling a more fine-grained edges to identify the subtle layering of the PBL.

2. BACKGROUND

The planetary boundary layer is the bottom layer of the atmosphere that is influenced by the Earth's surface.[12] It is an important component of climate and weather, and is used for air quality and pollution assessments as it is an important factor in understanding how pollutants are mixing near the surface.[13,14] As suggested by Stull et al.,[12] the PBL can be complex in nature and has variability. Accurate height calculation is of great importance, along with accurate simulation of the atmospheric properties contained within the PBL.[1]

3. RELATED WORK

Caicedo et al.[5] estimated PBLH using a Haar wavelet method applied to ceilometer backscatter profiles. Though their method was not machine learning based it did show a way to automatically process the gradient changes in the backscatter. Sleeman et al.[6] used a deep learning edge detection method to estimate PBLH. We build on this work to further improve deep edge detection. Work by Maroufidis et al.[15] built a segmentation model on MATLAB platform. They detected the aerosol layer and clouds using multiple thresholding with splitting. By partitioning the backscatter profiles they classify the layers using the intensity. With proven functionality of their work, their algorithm can only be implemented on MATLAB. Approaching the PBL detection with edge detection alone, tends to lose the finer details of aerosol layer. The segmentation is incorporated in PBL detection is to direct the HED[11] model to focus at the area with high probability of containing PBL in it. The collobaration of segmentation and HED[11] manages to excel both the tasks separately.[16]

4. PROPOSED APPROACH

HED[11] has five convolutional side output layers that represent different levels of abstraction. A loss function is used with each side output layer as depicted in Figure 2. These output layers are then fused together. The fusion is then combined with the convolutional network layer output of the normal path of the neural network to improve the edge detection. Each convolutional output layer represents a different perspective of the image and after fused produce a final output.

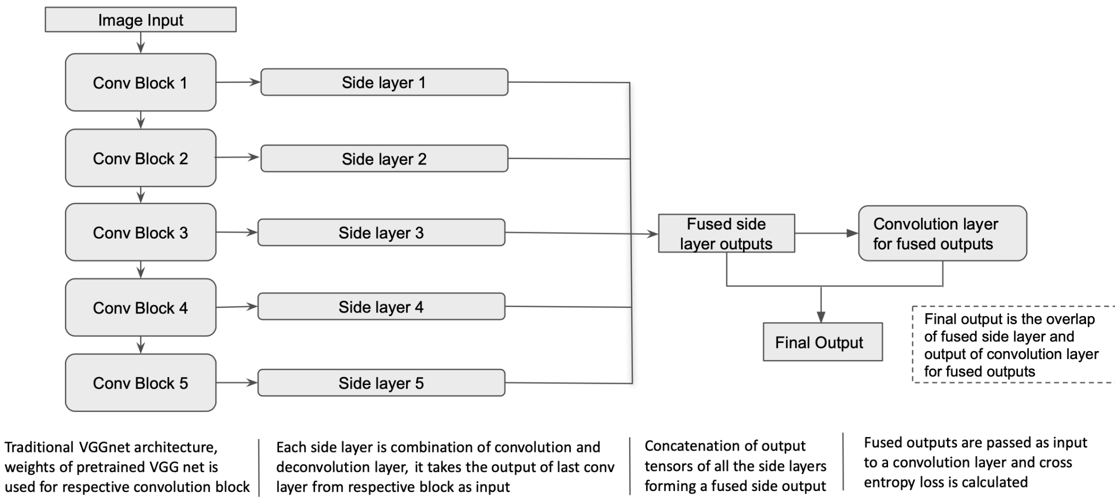

Figure 2. HED Network Architecture.

Details that are apparent in the early convolutional layers can get lost during the fusion because each output layer is treated equally during the fusion. We show an example of this problem in Figure 3. Problems begin to occur at different transition periods throughout the day and when there is layering among the PBL for a given time period. The processing of these edges lose significance in the downstream conversion of edges in pixel space to points in coordinate space.

To overcome this issue our approach is two-fold. First we encourage the network to focus on the part of the imagery where the PBL is present during training. Second we given more weight to layer 2 which contains much

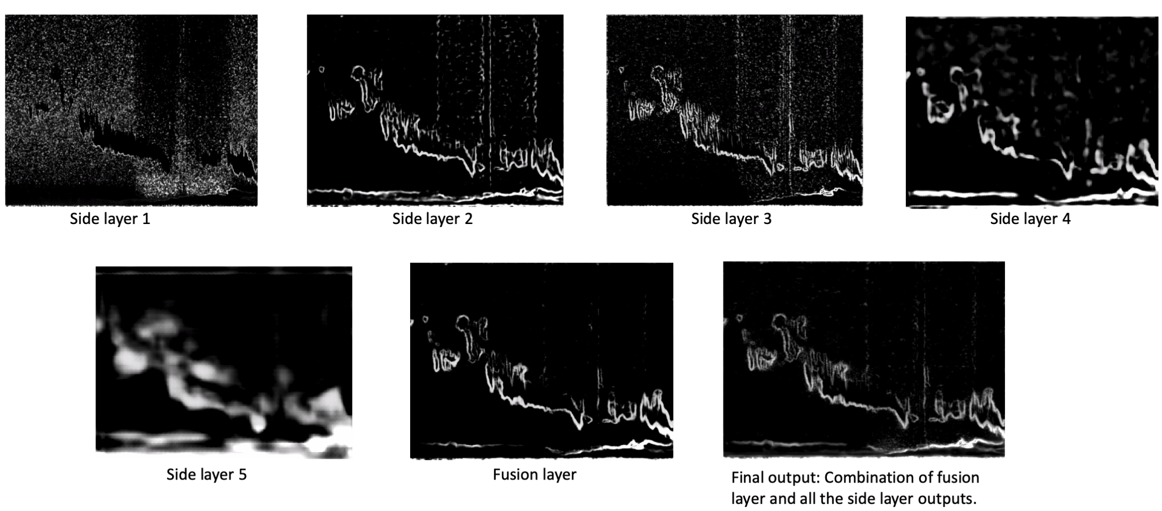

Figure 3. TensorFlow Trained HED Network Using the Berkley Dataset - A View of the Output Layers.

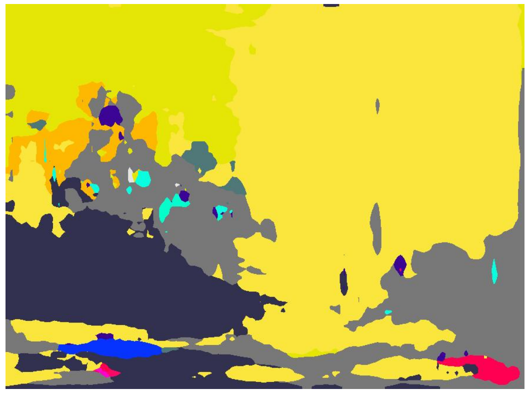

Figure 4. Lufft-CHM15K - Catonsville, MD - 24 Hour LIDAR Backscatter Profile Segmented 12/13/2016.

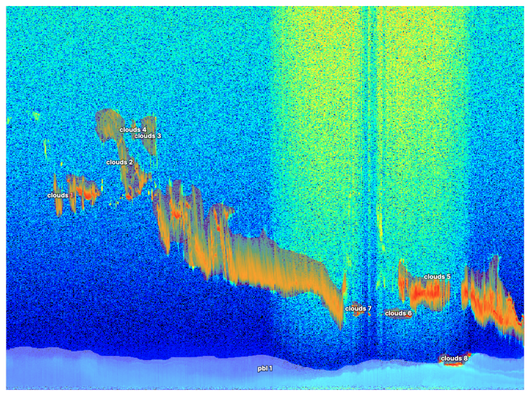

Figure 5. Lufft-CHM15K - Catonsville, MD - 24 Hour LIDAR Backscatter Profile Labeled for Training a Segmentation 12/13/2016.

of the detail present in the backscatter imagery. One method that we are currently exploring to approximate the location of the PBL is a segmentation network. The segmentation network takes as input the backscatter profiles to segment the image into approximate areas. An example of this output is shown in Figure 4.

The results shared in this paper are based on using the pretrained segmentation network, due to the lack of backscatter training data. However, we are currently developing a labeled dataset that can be used to train the segmentation network. This dataset is labeled used Labelbox (https://labelbox.com/). An example of the labeled data in shown in Figure 5.

Our future work will use the segmentation network trained using our labeled backscatter data. This dataset will also be useful for other tasks such as classification.

We use this estimation to direct the HED[11] learning process, by having the image information from masks extracted from the segmentation network, we use the recognized PBL max height as a threshold to be reduced any area above the threshold to black for one of the output layers, acting as an attention mechanism. In addition, we weight the second output layer higher than the other layers since this is where most of the detail is found with respect to the subtle PBL edges. With these two methods we are able to maintain the finer edges of the backscatter imagery.

After the edge detection method detects the boundaries in the imagery, the custom algorithm described in[6] is used to converts lines into points in pixel space and maps points in pixel space to points in coordinate space. This gives us the ability to convert edge detected boundaries into numeric values as derived heights at given points in time.

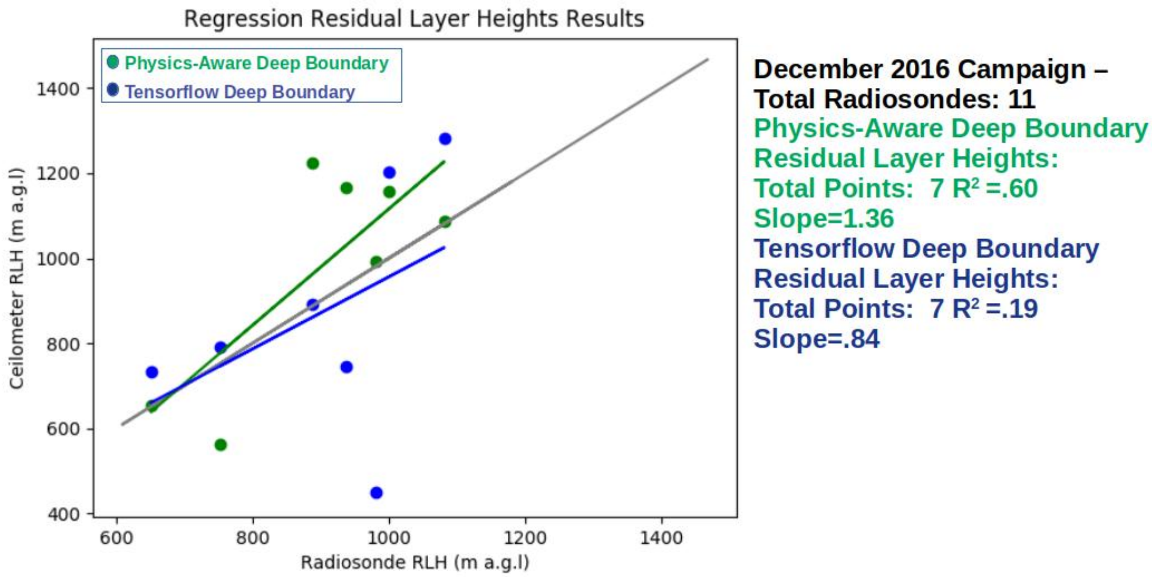

Figure 6. Linear Regression of the new physics-aware edge detections compared to the non-physics aware edge detection trained using Tensorflow for Lufft-CHM15K - Catonsville, MD - 24 Hour LIDAR Backscatter Profiles for December 2016.

5. EARLY RESULTS

Early experiments exploring the use of ceilometers for PBLH estimation include work by Caicedo et al.[5] and the deep learning efforts by Sleeman et al.[6] that was described as an augmentation to the wavelet method. As an extension to this work we perform an experimental comparison using the same campaign consisting of the LIDAR backscatter profiles from the Lufft CHM15k ceilometer located at the University of Maryland Baltimore County (UMBC) in Catonsville, Maryland (39.2544, -76.7095) between December 1, 2016 and December 15, 2016. However we focus on evaluating the residual layer and its associated radiosonde points from this campaign.

The experimental setup consisted of our new physics-aware deep edge detection network directed by our segmentation effort. We trained the network with BSD data and with 62 images we collected from 3 different ceilometers (all of which are Lufft-CHM15K) with locations in (Catonsville, MD, Bristol, PA, and Blackburg VA). The training data used from ceilometers was based on data collected from September 2020. We used the December 2016 data as our held-out set and generated edges from the backscatter images from December 1st - December 14th. We also trained an unmodified HED[11] network using the same Tensorflow framework and the BSD training data. We evaluated these methods by using the radiosonde points as ground truth and compared the edge-detected values with that of the radiosondes specifically for the residual layer. For this campaign, there were 11 timestamps where the residual layer was present with recorded radiosondes of which 7 of the backscatter profiles were available for edge generation. We show a linear regression of these results in Figure 6 where we compare the trained HED network[11] unmodified with our physics-aware HED network.

We also compared our method with the original Caffe HED[11] network, however, many of the residual layer timestamps referenced by the radiosondes had no edge detected. We conclude from this that our method made improvements over both the Caffe HED[11] network and the HED[11] network that was not physics-aware. For comparison we also trained the HED[11] network that was not physics-aware with ceilometer backscatter data in addition to the BSD data, however the results were poor.

In comparison with the side outputs of the HED[11] network that was not physics-aware shown in Figure 3, we show the outputs of the physics-aware HED network in Figure 7.

We also show an example of our edge detection obtained from the trained physics-aware HED[11] in comparison with output obtained from the pretraiend Caffe HED edge detection for December 13, 2016 in Figure 8. Clearly

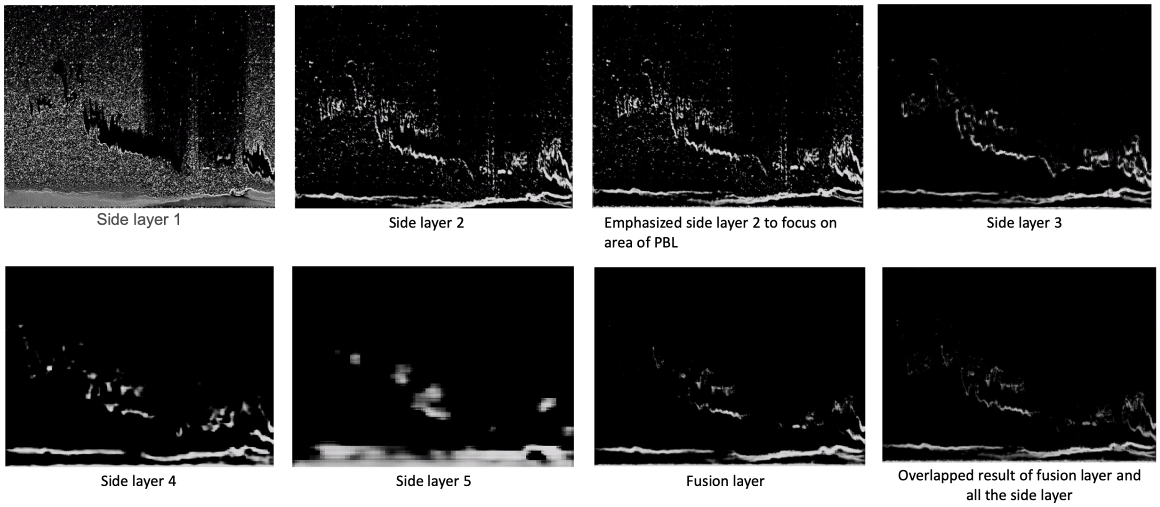

Figure 7. Physics-Aware TensorFlow Trained HED Network - A View of the Output Layers.

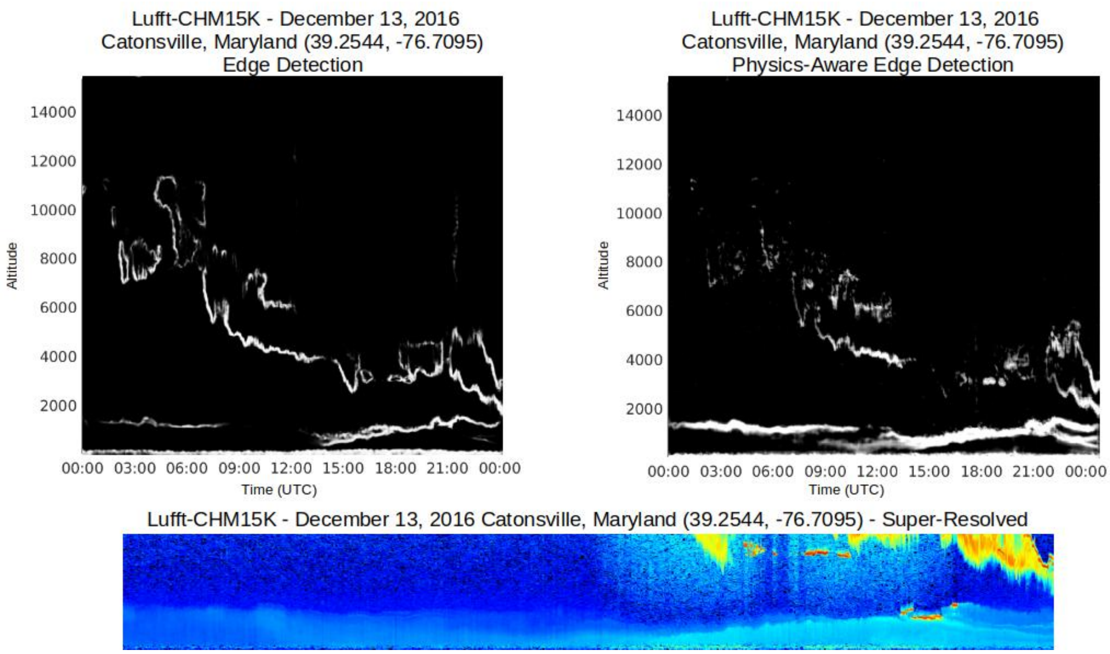

Figure 8. Comparing the original edge detections (left) with the new physics-aware edge detections (right) for Lufft-CHM15K - Catonsville, MD - 24 Hour LIDAR Backscatter Profile Segmented 12/13/2016.

more of the subtle edges are defined by the physics-aware HED network, when compared with the original HED network trained on BSD images.

6. CONCLUSIONS

This work describes the early effort to improve edge detection for automatic PBLH estimation. Though identifying edges using a pretrained HED network enables PBLH estimation, by directing the learning of the network to parts of the backscatter and giving that part of the backscatter attention, we can train the edge detector to also capture the more subtle edges that are typically present with residual and nocturnal layers of the PBL. The dataset that will results from this work will provide a basis for training future segmentation networks that could be used for segmentation and for classification.

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