APPLICATION OF DEEP LEARNING FOR IMAGING-BASED STREAM GAGING

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Introduction

The goal of water resource management is to develop methods to monitor and optimally allocate water resources across the various entities that require the resource. Stream gages are instruments that are typically capable of tracking the flow discharge and water height in a river or stream. According to the United States Geographical Survey, average operation cost was about $14,000 annually per typical continuous stream gage (Norris et al., 2007) with most cost associated with site inspections and field experiments. Therefore, a need arises in minimizing the cost for current stream gaging setups.

In addition to their vast stream gaging network, the USGS also maintains a network of webcams located at many stream gage sites. The webcam images and existing stream gage data can be utilized to create a new remote sensing method. This study will outline a method for developing an Image Regression Stream Gaging model that predicts river height from webcam data. This method will generate approximations of the actual river height value for some site. These approximations should lie within relative accuracy of the true height value. We wish to show that this process will create accurate stream gage results for a sample of USGS sites given sufficient data.

Data

Many USGS stations include live webcam images of the nearby river. Each webcam captures an image of the water body at a specific time interval. The camera angle, the position of the camera along the river, and the resolution of the images captured vary across the sites. Synchronizing the stream gage data and the image would be ideal to train a DNN to fit a prediction on an image to the actual stage height value. As a constantly maintained system, this system was able to capture data daily from March 2020 to January 2021. At the end of this process, 2,861 images from the Milwaukee River site, 6,777 images from the Clear Creek site, and 2,348 images from the Auglaize River site were acquired for this study. Pre-processing in the form of rescaling and random augmentation was performed on the images before use in the study.

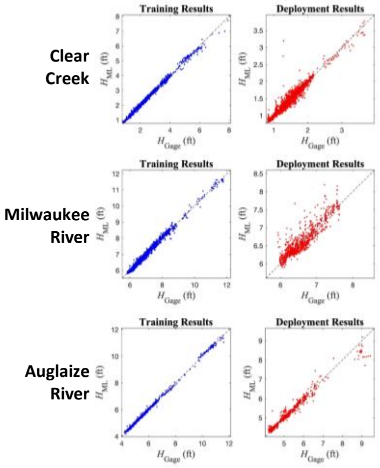
Method

With the data retrieved, the prediction of river stage based on image information can be formulated as a regression problem. Utilizing Transfer Learning and Image Regression, we can modify a popular Image Classification model to fit this problem. VGG-16 is chosen due to its stability in preliminary experiments (Simonyan et al., 2015). Since these models exist as Image Classification methods, these models are originally designed to output an array of class label probabilities. To fit the model for Image Regression, the fully-connected and output layers are modified to output a single scalar value. Gradient Descent with the Adam optimization algorithm is utilized to train the models (Kingma et al., 2015). Mean Squared Error is the loss function due to its ability to minimize extreme error cases. The stage height data is normalized to a mean height of 0. Training occurs for 20 iterations with the best performing model on the validation set saved for future use.

Figure 1: Selected Experiment Image Samples

Figure 2: Mean Saliency Maps from Trained Models

Figure 3: Real (Gage) vs Predicted (ML) values for Training and Deployment data



Results

In the Clear Creek dataset, the minimum MSE score for the validation set is 0.0046 ft^2 after 20 epochs. For the Milwaukee River dataset, the final MSE is 0.0152 ft^2.On the Auglaize River, the final MSE score is 0.0116 ft^2 . It is clear that this model creates an accurate prediction with average error within a few tenths of a feet. Therefore, the training process is effective at fitting the image data to predicting water stage.

To show how the model is making water height predictions, Saliency Mapping is employed on the model. Saliency mapping can be utilized to generate a "heatmap" of the most important pixels in an image. The average saliency map for the validation set is shown in Figure 2. From the mean saliency maps, the model tends focus on features with a clear correlation with the water height including shorelines, static structures, and rocks.

The deployment set is a dataset containing 90% of images gathered after a set date depending on the site. The goal of the deployment experiment is to simulate a field deployment and evaluate how the model reacts over time. Figure 3 shows a Real vs. Predicted values graph for the Training and Deployment dataset. As expected, the deployment set predictions are not as accurate as the predictions on the training set. However, all the deployment set predictions still correlate with the general trend of the time series.

Conclusion

This study serves as a proof-of-concept that river stage can be directly predicted from static images. The presented DNN regression model on stream gage webcam data shows potential as a general non-contact method of measuring river flow data, which minimizes the cost and hazards associated with the current operation. As a data-driven approach, the supervised training procedure can be universally applied to other sites without specific knowledge, parameter tuning, or manual calibration of a specific site. This study demonstrates the strength of machine learning if sufficient data are available for the learning process.

Literature Cited

Kingma, D., & Ba, J. (2015) Adam: A Method For Stochastic optimization. International Conference on Learning Representations, arXiv:1412.6980.
Norris, J. M., Lewis, M., Dorsey, M., Kimbrough, R., Holmes, R. R., & Staubitz, W. (2007). Qualitative comparison of streamflow information programs of the US Geological Survey and three non-federal agencies. US Geological Survey Open-File Report, 2007, 1426.
Simonyan, K., & Zisserman, A. (2015) Very deep convolutional networks for large-scale image recognition, International Conference on Learning Representations, arXiv:1409.1556.

Special Thanks to the United States Geological Survey. Data gathered is publicly available at https://apps.usgs.gov/sstl/