EECE 5644 Machine Learn/Pattern Recognition Spring 2019

Final Project Proposal: Aerial Image Labeling and Semantic segmentation

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1. What research issue(s) interest you most? Why?

Ever since the first aerial image became commercialized decades ago, many different applications for these images have been developed at an exponential growth. One such application lies with image classification and object detection of aerial imagery [3][4]. Image segmentation involves assigning a class label to every pixel in an overhead aerial image to determine different artifacts inside that image, such as buildings and roads [7]. Having these methods of image classification can bring many benefits throughout different industries interested in being able to procedurally detect artifacts in aerial imagery, such as the autonomous vehicle industry being able to use this application to determine precise road routing. In this project, we will review the different algorithms used on Aerial Image Labeling and Semantic segmentation as pertaining to deep convolutional neural networks, and how we can find other methods and improvements to the current methods, such as the use of unsupervised learning.

2. Who else has worked in this vein? What did they accomplish? What can't they do?

Geoffrey Hinton and his team have invented multi-layer neural networks. His work has been proven superior to other state-of-art algorithms, and has become the benchmark for image labeling and segmentation within the field [11]. However, his work involves using supervised learning on a large amount of training data, being processed with significant computational resources, meaning there is a restriction on what applications can use neural networks. Though there does seem to be some research into using unsupervised learning on basic imagery [10], this work still seems to be underdeveloped, and hasn't changed the standard for image classification.

3. What kind of progress would you like to see? Why?

Applications involved with image labeling are time consuming, and pixel-based semantic segmentation is even more demanding of sufficient training resources. We want to learn the advantage and disadvantage of different algorithms for processing image segmentation. Our main goal is to find a possible unsupervised learning method that can match or even beat the neural network approach on performance. If we can find a better alternative, then using aerial image labeling can be applied to a wider range of applications instead of only being possible in applications with a large amount of computational power.

4. Do you have an idea for making some such progress? Explain.

There are already some unsupervised learning algorithms used in image labeling such as Otsu's method (maximum variance)[8], and k-means clustering. We would implement one of these methods in our project. We would also look into other unsupervised methods that have yet to appear in public research, such as kernel PCA and LDA, and then compare with existing Convolutional Neural Network [6] model such as CNN - Deeplab v3+ and Resnet-18 [9].

5. What do you expect to discover from your investigation?

By the end of this project, we will attempt to implement image-labeling and segmentation through Matlab [1][2]. We will compare and analysis the result of our implementation against the available benchmarks of other methods. We will expect to understand the fundamental differences and limitations of different types of supervised versus unsupervised machine learning algorithms, and see if the newer methods of image labeling are comparable to the methods standard in the field today. Our hypothesis is that unsupervised learning will perform with similar accuracy.

6. How will your expected result(s) affect the research community?

The standard practice of image-labeling and semantic segmentation is through the use of deep neural networks. Semantic segmentation modeling based on convolutional neural networks (CNN) [6][9]at a pixel level may achieve average pixel accuracy of 96.08% [5][8]. We hope that our project will find a viable alternative to using neural networks through the use of unsupervised learning, and that using unsupervised learning methods can also compete in both performance and resources required. We hope that our results can change and improve the standard of image-labeling and semantic segmentation.

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