COMP2550/COMP3130 ANU Warmup Project Report

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1 Introduction and Overview

The field of computer vision is often thought of as a diverse topic, however in reality there are three major paths to which each project can be linked. The first two, scene categorisation and object detection, aim to provide a summary of a scene using tags and to detect discrete objects within an image respectively, however do not deliver an accurate object outline nor consider the image as a whole such as what happens in one portion of human vision. The task at hand for this warmup project was to further the third path of annotating an entire image at the pixel level, by considering a unified cluster of pixels as a superpixel and extracting a set of useful features to check against using the open source Darwin framework for machine learning and the MSRC dataset. The desired outcome was a feature vector that allowed machine learning algorithms to classify images with over 50% accuracy.

2 Method

The first few features implemented were the average red, green and blue values of the superpixel, since this would begin to differentiate between extremely different superpixels, such as those describing sky and grass. Adding in the standard deviation of these colours could also help differentiate between differently textured models. We also tried out getting the difference and absolute difference between the red, green and blue average values across the superpixel to further bring out features dependent on the superpixel composition. Other features tested include the average gradient in the superpixel, its centre to know the general location within the image (to help differentiate between sky and water for example), and taking into consideration the differences between the superpixel's immediate neighbours and itself, intuitively approximating the outlines of objects to help the classifier decide what superpixels are more likely to be when in close proximity to superpixels of another type.

3 Results

Pictures, maybe accuracy tables with different features implemented?

4 Discussion

numerical analysis of your algorithm - accuracy, number of features, efficiency/running-time estimate, see how this changes with certain algorithm parameters (eg number of features, depth of decision tree, broken down by class, etc) What is the performance of your algorithm on the training set compared to the test set? Is this result expected?
Why is it important to evaluate pixelwise accuracy instead of accuracy on the superpixels?
What do you think is more important, the features or the machine learning classifier?
Interpretation of results, what went well, what went wrong (overfitting?), what could be done better.

5 References

S. Gould. DARWIN: A Framework for Machine Learning and Computer Vision Research and Development. In *Journal of Machine Learning Research (JMLR)*, 2012.
K. Park and S. Gould. On Learning Higher-Order Consistency Potentials for Multi-class Pixel Labeling. In *Proceedings of the European Conference on Computer Vision (ECCV)*, 2012.