SSD Clustering

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February 13, 2022

Abstract

1 Introduction

The premise of this investigation is to use a form of clustering to drive the training of deep learning models. With clusters, we hope to promote small intra-cluster variability and reduce the need for large capacity models by training a model for each cluster. With that a corresponding reducing in the amount of training data.

2 Clustering

There are two distinct set of approaches to our clustering:

1. cluster the input images
   (a) simple region covariance 2.1.1
   (b) some form of non-Local Means (NLM)
2. cluster the feature vectors of a pre-trained model

There the algorithm to perform the clustering also deserve some investigation. K-means is certain a starting point but it is very sensitive to initialization. Next, the question of producing a quasi balanced cluster should also be considered.

If we are using a NLM approach, naive approach will make k passes for k clusters while testing for nearest center. At least we need a fast lookup structure so that the nearest center can be retrieved in $O(logn)$ or $O(1)$ time. Or use the very nice SigmaSet 2.1.2 or [KH10]

2.1 Region Covariance

Region covariance can be computed very efficiently using 'integral images/-sumarea table" [PT06].

Using covariance improves computer detection and tracking of humans

2.1.1 [TPM06]

"Region covariance: A fast descriptor for detection and classification"

2.1.2 Sigma set

[HCS+09]

2.2 Kwatra2010

"Fast Covariance Computation and Dimensionality Reduction for Sub-Window Features in Images"

2.2.1 Faulkner2015

[FSS+15] "A Study of the Region Covariance Descriptor: Impact of Feature Selection and Image Transformations"

2.3 Non-Local Means

2.3.1 Qian2013

[QY13] nonlocal similarity and spectral-spatial structure of hyperspectral imagery into sparse representation. Non-locality means the self-similarity of image, by which a whole image can be partitioned into some groups containing similar patches. The similar patches in each group are sparsely represented with a shared subset of atoms in a dictionary making true signal and noise more easily separated.

2.3.2 Fu2017

[FLSS17]

3 SSD

4 Conclusion

5 Remarks

Acknowledgments. Finally, thank you to my family and friends for the support during this report.

References

[FLSS17] Ying Fu, Antony Lam, Imari Sato, and Yoichi Sato. Adaptive Spatial-Spectral Dictionary Learning for Hyperspectral Image Restoration. *Int J of Computer Vision*, 122(2):228–245, 2017.

[FSS+15] Hayden Faulkner, Ergnoor Shehu, Zygmunt L. Szpak, Wojciech Chojnacki, Jules R. Tapamo, Anthony Dick, and Anton Van Den Hengel. A Study of the Region Covariance Descriptor: Impact of Feature Selection and Image Transformations. In *DICTA '15*, page 8, 2015.

[HCS+09] Xiaopeng Hong, Hong Chang, Shiguang Shan, Xilin Chen, and Wen Gao. Sigma set: A small second order statistical region descriptor. In *CVPR Workshops '09*, pages 1802–1809. Ieee, jun 2009.

[KH10] Vivek Kwatra and Mei Han. Fast covariance computation and dimensionality reduction for sub-window features in images. In *ECCV 2010*, volume 94043, 2010.

[PT06] Fatih Porikli and Oncel Tuzel. Fast construction of covariance matrices for arbitrary size image windows. *ICIP '06*, pages 1581–1584, 2006.

[QY13] Yuntao Qian and Minchao Ye. Hyperspectral imagery restoration using nonlocal spectral-spatial structured sparse representation with noise estimation. *IEEE J of Selected Topics in Applied Earth Observations and Remote Sensing*, 6(2):499–515, 2013.

[TPM06] Oncel Tuzel, Fatih Porikli, and Peter Meer. Region covariance: A fast descriptor for detection and classification. In *ECCV '06*, pages 589–600, 2006.