TEXTURE SEGMENTATION

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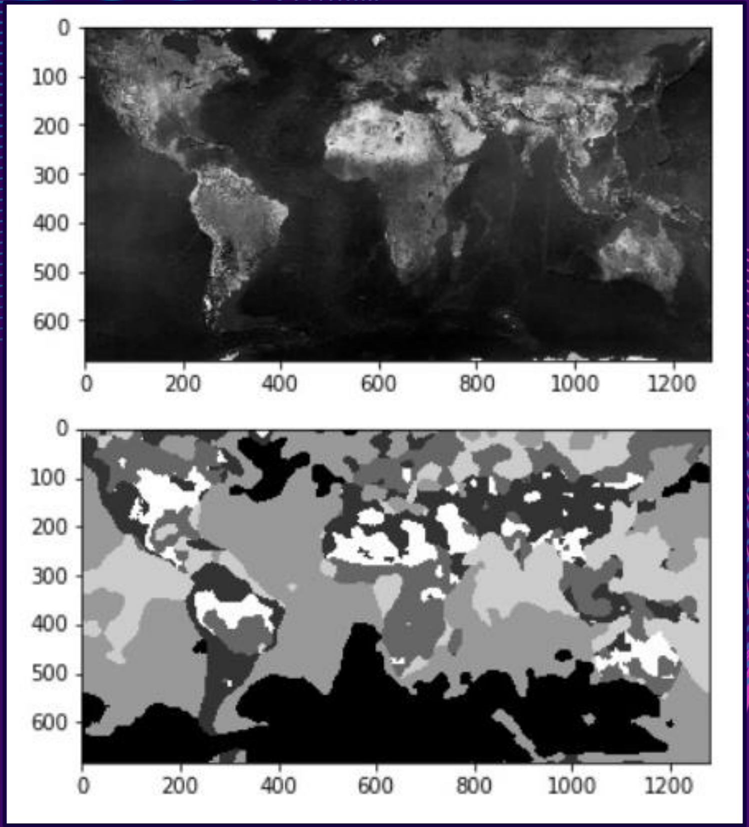
PROBLEM

Texture Segmentation using Matrix Decomposition Techniques



METHODS IMPLEMENTED

SPECTRAL HISTOGRAM

After creating histograms based on pixel intensities, we add filters to them to make it more efficient. In our project we have used Laplacian of Gaussian filter and Gabor Filter to form spatial patterns, which better differentiate texture appearances. Histograms of multiple filter responses are computed and concatenated. These are called spectral histograms.

LOW RANK APPROXIMATION

Now from the spectral histograms, to compute the segments, the representative feature matrix and combinational weights are unknown, Here, the rank of feature matrix will be equal to that of representative feature matrix. We perform SVD functions on the feature matrix to get unique segments.

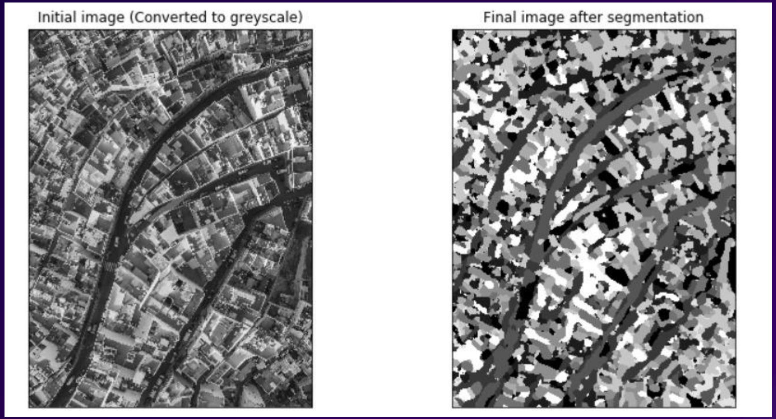
SINGULAR VALUE DECOMPOSITION

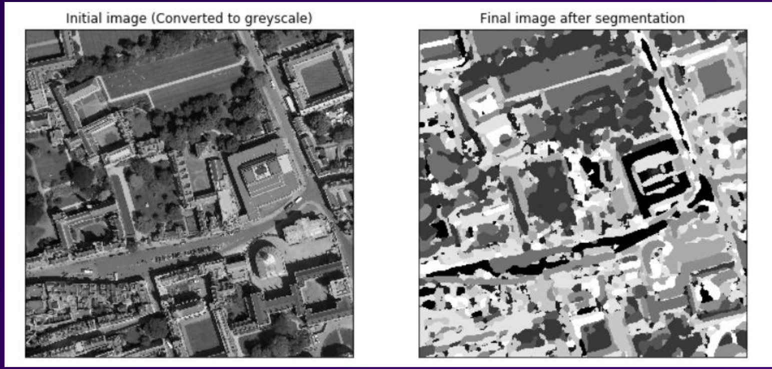
Images can be noisy, and here we convert the feature matrix and combinational weights to a lower dimension by choosing the ‘r’ number of largest singular values to get a feature matrix of rank ‘r’. Then SVD is performed, followed by k-means clustering to get the segmentation results, after removing noise and dealing with edges.

NON-NEGATIVITY CONSTRAINTS

Along with SVD, we impose some constraints on the algorithm. This is because the combination weights of the features represent the coverage fraction of its local window. Hence the weights should be nonnegative, and the sum of weights for each feature should be one.

EXPERIMENTAL RESULTS





CONCLUSION

In this paper we've presented an effective, fast and simple algorithm to segment pictures, which uses local histograms as features. It considers the process as a matrix factorization task and following partial SVD, taking linear time to perform segmentation.

Since we used different matrix factorization techniques to bring the features to a low dimensionality subspace, it makes calculation of the invertible matrix Q faster, which in turn makes calculation of end representative feature clustering faster and reliable. The results from the experiment shows that the proposed method performs well.

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