Advanced Image Processing Project

2019-2020

Project Objective

Incorporate texture information into region-based superpixels segmentation.

Project description

Superpixels is an unsupervised image segmentation technique. There are several implementations that output a desired number of regular, compact superpixels with a low computational overhead. However, the texture cues, are rarely considered.

In this project, the students are invited to incorporate texture information into the SLIC algorithm. The performance of the proposed framework should be evaluated on a subset of Berkeley Dataset (BSDS 500).

Project Details

Superpixel description

A superpixel can be defined as a group of pixels which have similar characteristics. It is generally color based segmentation. Superpixels can be very helpful for image segmentation. There are many algorithms available to segment superpixels but SLIC is state-of-the-art with low computational overhead.

SLIC

Simple Linear Iterative Clustering is the state of the art algorithm to segment superpixels which doesn't require much computational power. In brief, the algorithm clusters pixels in the combined five-dimensional color and image plane space to efficiently generate compact, nearly uniform superpixels. This algorithm was developed at Image and Visual Representation Group (IVRG) at EPFL and the published paper in [1] and official source code in [2].

How does SLIC work?

The approach is very simple. SLIC performs a local clustering of pixels in 5-D space defined by the L, a, b values of the CIELAB colorspace and x, y coordinates of the pixels. It has a different distance measurement which enables compactness and regularity in the superpixel shapes and can be used on grayscale images as well as color images.

SLIC generates superpixels by clustering pixels based on their color similarity and proximity in the image plane. A 5 dimensional [labxy] space is used for clustering. CIELAB color space is considered as perpetually uniform for small color distances. It is not advisable to simply use Euclidean distance in the

5D space and hence the authors have introduced a new distance measure that considers superpixels size.

Distance Measure

SLIC takes a desired number of approximately equally-sized superpixels K as input. So each superpixel will have approximately N/K pixels. Hence, for equally sized superpixels, there would be a superpixel center at every grid interval $S = \sqrt{N/K}$

K superpixel cluster centers $c_K = [l_k, a_k, b_k, x_k, y_k]$ with $k = [1, K]$ at regular grid intervals S are chosen. Since the spatial extent of any cluster is approximately S^2, it can be assumed that pixels associated with this cluster lie within 2S x 2S area around the superpixel center in the xy plane.

Euclidean distances in CIELAB color space are meaningful for small distances. If spatial pixel distances exceed this perceptual color distance limit, then they begin to outweigh pixel color similarities.

Distance measure D_S is defined as follows.

$$d_{lab} = \sqrt{(l_k - l_i)^2 + (a_k - a_i)^2 + (b_k - b_i)^2}$$
$$d_{xy} = \sqrt{(x_k - x_i)^2 + (y_k - y_i)^2}$$
$$D_s = d_{lab} + \frac{m}{S} d_{xy} ,$$

Where D_s is the sum of the lab distance and the xy plane distance normalized by the grid interval S. A variable m is introduced in D_s allowing us to control the compactness of superpixel. The greater the value of m, the more spatial proximity is emphasized and the more compact the cluster. This value can be in the range [1, 20]. Authors of the algorithm have chosen m=10.

Algorithm

It begins by sampling K regularly spaced cluster centers and moving them to seed locations corresponding to the lowest gradient position in a 3 × 3 neighborhood. This is done to avoid placing them at an edge and to reduce the chances of choosing a noisy pixel. Image gradients are computed as

$$G(x,y) = \|\mathbf{I}(x+1,y) - \mathbf{I}(x-1,y)\|^2 + \|\mathbf{I}(x,y+1) - \mathbf{I}(x,y-1)\|^2$$

Where I(x, y) is the lab vector corresponding to the pixel at position (x, y), and ||.|| is the L2 norm. This takes into account both color and intensity information.

Each pixel in the image is associated with the nearest cluster center whose search area overlaps this pixel. After all the pixels are associated with the nearest cluster center, a new center is computed as the average labxy vector of all the pixels belonging to the cluster.

At the end of this process, a few stray labels may remain, that is, a few pixels in the vicinity of a larger segment having the same label but not connected to it. It enforces connectivity in the last step of the algorithm by relabeling disjoint segments with the labels of the largest neighboring cluster.

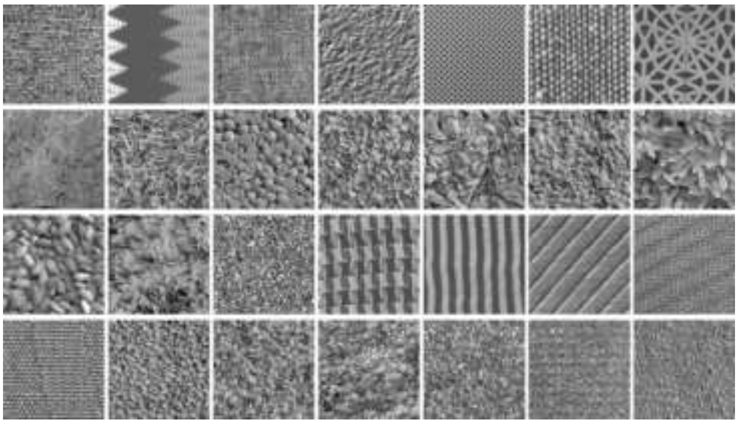
Algorithm 1 Efficient superpixel segmentation

Initialize cluster centers $C_k = [l_k, a_k, b_k, x_k, y_k]^T$ by sampling pixels at regular grid steps S.
Perturb cluster centers in an $n \times n$ neighborhood, to the lowest gradient position.
repeat
    for each cluster center C_k **do**
        Assign the best matching pixels from a $2S \times 2S$ square neighborhood around the cluster center according to the distance measure (Eq. 1).
    end for
    Compute new cluster centers and residual error E {$L1$ distance between previous centers and recomputed centers}
until $E \leq$ threshold
Enforce connectivity.

Image Texture:

A texture is a set of repetitive patterns that have the same characteristics. Image texture gives us information about the spatial arrangement of color or intensities in an image or selected region of an image.

Several metrics could be calculated in image processing to quantify the perceived texture of an image like Co-occurrence Matrix (GLCM) [3] or Local Binary Patterns (LBP) [4] or laws texture energy measures [5], etc. In the coming lectures, we will study in details the different families of approaches for texture analysis.



References:

[1]: Achanta, R., Shaji, A., Smith, K., Lucchi, A., Fua, P., & Süsstrunk, S. (2010). *Slic superpixels* (No. EPFL-REPORT-149300).

[2]:ivrg.epfl.ch/files/content/sites/ivrg/files/supplementary_material/RK_SLICsuperpixels/SLICSuperpixelsAndSupervoxelsCode.zip

[3]: Haralick, R. M., & Shanmugam, K. (1973). Textural features for image classification. IEEE Transactions on systems, man, and cybernetics, (6), 610-621.

[4] Ojala, T., Pietikainen, M., & Maenpaa, T. (2002). Multiresolution gray-scale and rotation invariant texture classification with local binary patterns. *IEEE Transactions on pattern analysis and machine intelligence*, *24*(7), 971-987.

[5]: Laws, K. I. (1980). *Textured image segmentation* (No. USCIPI-940). University of Southern California Los Angeles Image Processing INST.