Graph based Image Segmentation using improved SLIC Superpixel algorithm

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Abstract

Image processing refers to a variety of techniques that are used to maximize the information yield from a picture, in which input is an image and output may be image or characteristics/features associated with the image. One of popular image processing technique is image segmentation. The goal of image segmentation is to partition an image with N pixels into disjoint sets of pixels called clusters. Many methods have been proposed in the last few years for gray scale and color images. The SLIC (Simple Linear Iterative Clustering) segmentation technique has significance on RGB image for the simplicity of SLIC algorithm makes it extremely easy to use. A downside to many superpixel segmentation algorithms is the need for parameter tuning. SLIC requires two input parameters, a compactness factor m and the number of clusters k. we have Estimated the number of clusters k for SLIC for image segmentation using Elbow method. Then we have compared proposed SLIC algorithm with the three other techniques are Quickshift, Felzenswalb, WaterShed with normal image and a noisy image. Among all these algorithms SLIC is giving better performance for both normal and noisy images.

Keywords: *Segmentation; SLIC; Elbow Method*

Introduction:

Image processing is the general issue in today's era, when we work with computer vision. It is in itself, a broad view to be considered. In order to process the image, we need to segment it so that it would become easier for the computer to understand. Image segmentation is the process of segmenting the image into various segments, that could be used for the further applications such as: Image understanding model, Robotics, Image analysis, Medical diagnosis, etc. Image segmentation is the process of partitioning an image into multiple segments, so as to change the representation of an image into something that is more meaningful and easier to analyze. Segmentation technique, basically convert the complex image into a simple image.

Watershed segmetation [3][4] technique find watershed basins in image flooded from given markers. The main disadvantage of the Watershed Transform is that for most natural images it produces excessive over-segmentation

Quckshift [2] Segments image using quickshift clustering in Color-(x,y) space. Produces an oversegmentation of the image using the quickshift mode-seeking algorithm. It strongly depends on the kernel size which can impact the clusters.

Felsenszwalb [1] efficient graph based image segmentation which roduces an oversegmentation of a multichannel image using a fast, minimum spanning tree based clustering on the image grid. The parameter scale sets an observation level. Higher scale means less and larger segments. sigma is the diameter of a Gaussian kernel, used for smoothing the image prior to segmentation.

The number of produced segments as well as their size can only be controlled indirectly through scale. Segment size within an image can vary greatly depending on local contrast. For RGB images, the algorithm uses the euclidean distance between pixels in color space.

SLIC (Simple Iterative Linear Clustering) [5] is another segmentation technique which segment the image based on number of super pixels specified. The simplicity of this approach makes it extremely easy to use – a lone parameter specifies the number of superpixels – and the efficiency of the algorithm makes it very practical. In this paper, to specify the number of super pixels in SLIC algorithm, Elbow method is used.

Existing Methodologies :

Watershed segmentation: The watershed is a classical algorithm used for segmentation, that is, for separating divergent objects in an image. Starting from user-defined markers, the watershed algorithm treats pixels values as a local topography (elevation). The algorithm floods basins from the markers, until basins attributed to different markers meet on watershed lines. In many cases, markers are chosen as local minima of the image, from which basins are flooded.

Quick shift is a fast mode seeking algorithm, similar to mean shift. The algorithm segments an RGB image (or any image with more than one channel) by identifying clusters of pixels in the joint spatial and color dimensions. Segments are local (superpixels) and can be used as a basis for further processing. Given an image, the algorithm calculates a forest of pixels whose branches are labelled with a distance value (vl_quickshift_get_parents, vl_quickshift_get_dists). This specifies a hierarchical segmentation of the image, with segments corresponding to subtrees. Useful superpixels can be identified by cutting the branches whose distance label is above a given threshold (the threshold can be either fixed by hand, or determined by cross validation).

Felsenszwalb's is an efficient graph based image segmentation. Produces an over segmentation of a multichannel (i.e. RGB) image using a fast, minimum spanning tree based clustering on the image grid. The parameter scale sets an observation level. Higher scale means less and larger segments. sigma is the diameter of a Gaussian kernel, used for smoothing the image prior to segmentation. The number of produced segments as well as their size can only be controlled indirectly through scale. Segment size within an image can vary greatly depending on local contrast. For RGB images, the algorithm uses the euclidean distance between pixels in color space.

Simple Linear Iterative Clustering (SLIC) 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. 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 gray scale images as well as color images. SLIC generates superpixels by clustering pixels based on their color similarity and proximity in the image plane. 1) initialize k cluster centers. 2) Find lowest gradient position in neighbourhood and update the seed locations to local maxima. 3) Compute image gradients based on color and intensity. 4) Assign each pixel to nearest cluster center. 5) Compute average of all pixels in the formed cluster. 6) Dijoint segments are relabelled to the largest neighbouring segment. Repeat the steps until all unlabeled pixels are labelled.

Proposed Method:

The SLIC segmentation algorithm is a novel approach deals with super pixels. The cluster pixels are combined in five dimensional color and image plane space to efficiently generate compact, nearly uniform superpixels. The simplicity of our approach called Elbow method makes it extremely easy to use and the efficiency of the algorithm makes it very practical. SLIC depends on a lone parameter specifies the number of superpixels. This parameter K can be obtained using Elbow method.

The idea of this project is to run SLIC segmentation on the image data for a range of values of k, and for each value of k calculate sum of squared errors. Sum of squared errors is the squared difference between actual data points and obtained segmented values.

Then, plot a line chart of the SSE for each value of k. If the line chart looks like an arm, then the "elbow" on the arm is the value of k that is the best. The idea is that we want a small SSE, but that the SSE tends to decrease toward 0 as we increase k (the SSE is 0 when k is equal to the number of data points in the dataset, because then each data point is its own cluster, and there is no error between it and the center of its cluster). So our goal is to choose a small value of k that still has a low SSE, and the elbow usually represents where we start to have diminishing returns by increasing k.

However, the elbow method doesn't always work well; especially if the data is not very clustered. Notice some data sets does not have a clear elbow. Instead, we see a fairly smooth curve, and it's unclear what is the best value of k to choose. In this case try a new valued range for k so that it produces a clear Elbow chart. The standard segmentation algorithms watershed, Quickshift, Felzenswalb are executed for comparing the results with SLIC.

Modified SLIC algorithm:

1) Take K cluster centers obtained from Elbow method

2) Find lowest gradient position in neighbourhood and update the seed locations to local maxima

3) Compute image gradients based on color and intensity

4) Assign each pixel to nearest cluster center

5) Compute average of all pixels in the formed cluster

6) Dijoint segments are relabelled to the largest neighbouring segment. Repeat the steps untill all unlabeled pixels are labelled.

Also in this paper comparison of segmentation techniques performance on noisy image is done. For this, some noise is added to the image manually and mean squared error is calculated for every segmentation. The experimentation shown that SLIC segmentation with elbow method's k value is giving less error compared to other techniques. The next best is given by watershed segmentation technique since it depends on sobel filter. So before segmenting the image, Sobel filter is applied for noise cancellation. Quick shift and Felzenswalb are not upto mark compared with the other two for a noisy image.

Experimentation and results:

Considered color image with 321 X 481 size for implementing the followed image segmentation techniques Watershed, Quickshift, Felzenswalb and SLIC. To find segmentation accuracy, we have considered MSE (Mean Squared Error). Results experimented on 8 GB RAM with i5 processor with python as programming language.

Fig 1 :Original Image

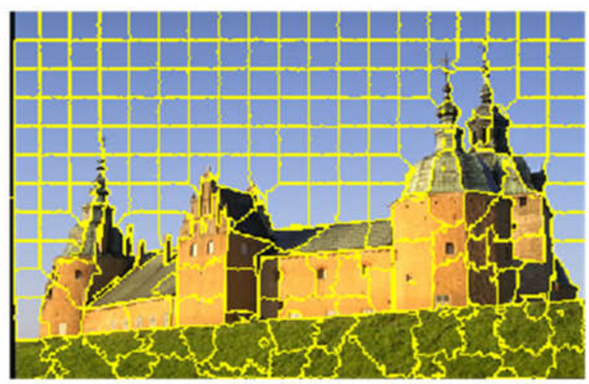

Fig 2 :Watershed Segmentation:

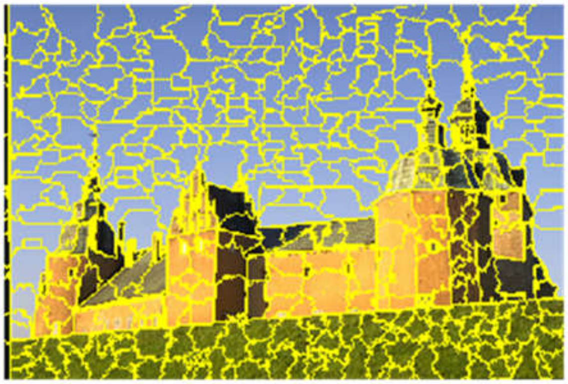

Fig 3: Quickshift Segmentation

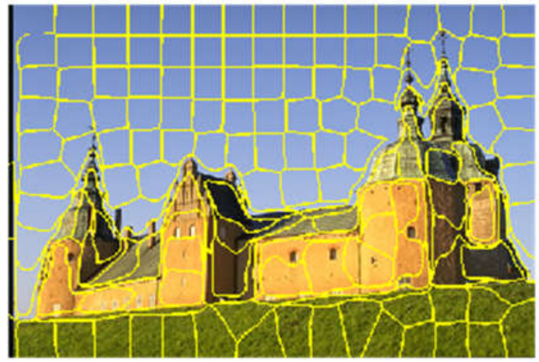

Fig 6: SLIC with 200 segments

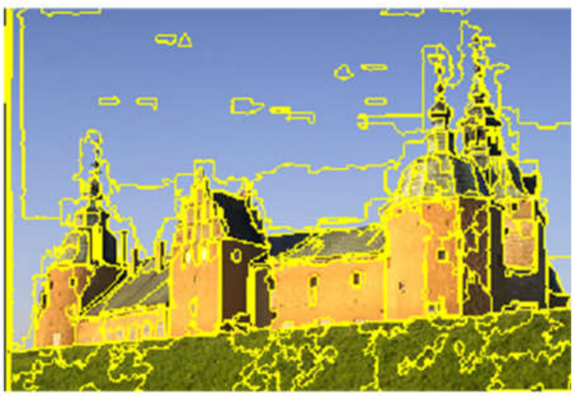

Fig 4: Felzenwalb's Segmentation:

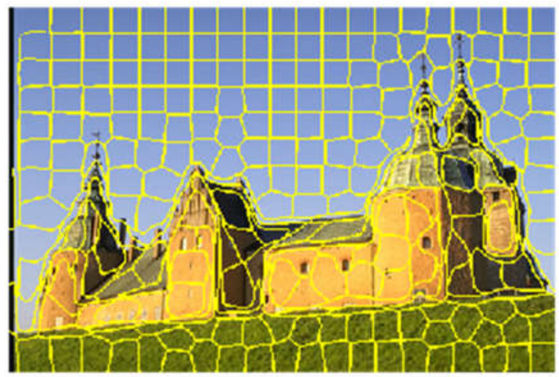

Fig 7: SLIC with 300 segments

Fig 5: SLIC with 100 segments

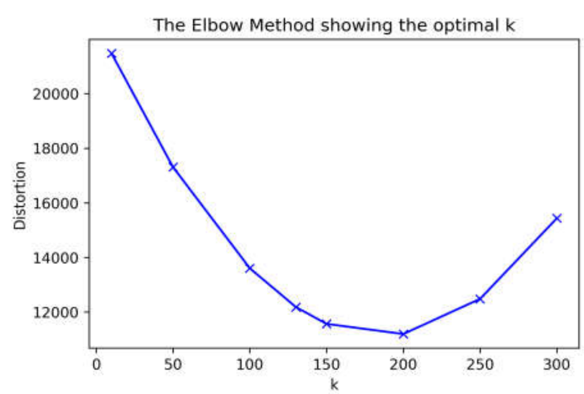

Fig 8: Elbow Method

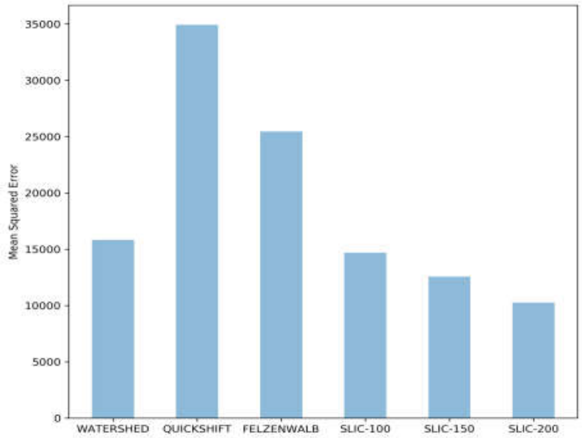

Fig 9 : Graph with MSE for segmentations

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