Image Segmentation Using Superpixel Based Split and Merge Method

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Abstract
A super pixel can be defined as a group of pixels, which have similar characteristics, which can be very helpful for image segmentation. It is generally color based segmentation as well as other features like texture, statistics…etc .There are many algorithms available to segment super pixels like Simple Linear Iterative Clustering (SLIC) super pixels and Density-Based Spatial Clustering of Application with Noise (DBSCAN). SLIC algorithm essentially relay on choosing N random or regular seeds points covering the used image for segmentation. In this paper Split and Merge algorithm was used instead to overcome determination the seed point's location and numbers as well as other used parameters. The overall results were better from the SLIC method depending on single threshold, which control the segments number needed (like 0.2) to accomplish the task.

Keywords: super pixels, image Segmentation, graph cut

انقسام الصورة باستخدام عناصر الصورة المميزة استناداً لطريقة الانشقاق والدمج

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الخلاصة:
يُمْكِنُ أَنْ تُعرّفَ super pixel (عناصر الصورة المميزة) كمجموعة عناصر الصورة التي لَها خصائصُ متماثلةُ، التي يُمكنُ أَنْ تَكُونَ طريقة مساعدة جداً لتجزئة الصورةِ. ويعتبر اللونُ عموما كأساس لعملية التجزئة هذه بالاضافة الى المميزات الاخرى(كالنسجة,المميزات الاحصائية ..الخ) . هناك العديد مِنْ الخوارزمياتِ المتوفرةِ لتَقسيم لتجزئة الصورة مثل SLIC و خوارزميةً التعنقد المكاني للتطبيقات اعتمادا على الكثافة اللونية بوجود الضوضاء DBSCAN (*Density-Based Spatial Clustering of Application with Noise*) . تعتمد خوارزميةُ SLIC اساساً على إخْتيارَعدد (n) من النقاط العشوائية أو المنتظمة والتي تغطي فضاء الصورةِ المستعملةِ لغرض تجزئة الصورة الى اجزاء لها صفات مميزة. في هذا البحث تم استخدام خوارزميةَ التقسيم والدمج (split & merge) لتَحديد مواقع النقاط واعدادها عوضا عن العشوائية في الخوارزمية السابقة بالاضافة الى التخلص من بعض المتغيرات الواجب تحديدها من قبل المستخدم لكل صورة (حسب طبيعة الصورة). و كَانتْ النتائج أفضل مِنْ الطريقة القياسية SLIC مع الاحتياج الى تحديد قيمة عتبة (threshold) ملائمة والتي بدورها تتحكم بعدد تقسيمات الصورة مثل (0.2) وغيرها لانجاز المهمّة.

Introduction

Image segmentation is a fundamental low-level vision problem with a great potential in applications. While human can parse an image into coherent regions easily, it is found rather difficult for automatic

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vision systems. Despite a variety of segmentation, techniques have been proposed, challenging remains for any single method to do segmentation successfully due to the broad diversity and ambiguity of visual patterns in a natural image [1] .Any segmentation of an image into contiguous regions could produce superpixels; candidate algorithms include watershed methods [2], [3]. Or Markov Random Field Models [4].

The main task of segmentation is to automatically recognize predefined labels (i.e. human, vehicle, grass, sky and etc) [5] . Superpixels, also known as regions in an over segmentation of the image, would be more natural and presumably lead to more efficient processing. The super pixel method had been increasingly used in image processing field, which can group pixels using the degree of feature similarity between pixels and acquire the redundant information of the image. Hence, it can greatly reduce the complexity of image post-processing tasks [6].

Superpixels are becoming increasingly popular for use in computer vision applications. Segmentation provides the partial support for computing region based features. The desired properties of superpixels segmentation depends on the application of interest. Here we list some general properties required by various vision applications [7], [8].

The following properties are generally desirable:

1) Superpixels should adhere well to image boundaries.

2) When used to reduce computational complexity as a preprocessing step, superpixels should be fast to compute, memory efficient, and simple to use.

3) When used for segmentation purposes, superpixels should both increase the speed and improve the quality of the results [9].

Simple linear iterative clustering (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) [1].

SLIC uses the same compactness. Parameter (chosen by user) for all superpixels in the image. If the image is smooth in certain regions but highly textured in others, SLIC produces smooth regular-sized superpixels in the smooth regions and highly irregular superpixels in the textured regions. So, it become tricky choosing the right parameter for each image [7], [8].

How does SLIC work?

The Simple Linear Iterative Clustering (SLIC) algorithm for superpixel segmentation is proposed in. an example of segmentation result is shown in figure 1. The SLIC superpixel segmentation algorithm is a k-means-based local clustering of pixels in the 5-D [lab; xy] space defined by the (L; a; b) values of the Commission International Éclair age, hence its CIE initialize (CIELAB) color space and the x; y pixel coordinates [7]. The reason why CIELAB color space is chosen is that it is perceptually uniform for small color distance. Instead of directly using the Euclidean distance in this 5-D space, SLIC introduce a new distance measure that considers superpixels size by taking into account a different weighting factor for chromaticity and locality. Distance measure D_s is defined as:

$$\text{dlab} = \sqrt{(l_k - l_i)^2 + (a_k - a_i)^2 + (b_k - b_i)^2}$$

$$d_{xy} = \sqrt{(x_k - x_i)^2 + (y_k - y_i)^2}$$

$$D_s = d_{lab} + m/S \text{ dxy}$$

Where Ds is the sum of the lab distance and the(x y) plane distance normalized by the grid interval S. A variable m is introduced in D_s allowing us to control the compactness of superpixels. The greater the value of m, the more spatial proximity is emphasized and the more compact the cluster [11].

Figure 1-Represents the output of SLIC algorithm with a constant compactness Factor for all superpixels [7].

Algorithm: SLIC superpixels segmentation

The standard algorithm for SLIC method can be given by the following steps [7].

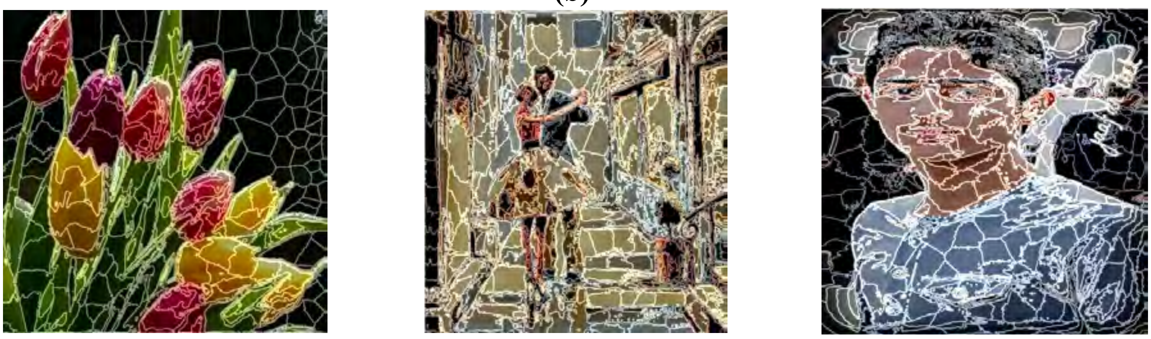
1: Initialize cluster centers $[lk; ak; bk; xk; yk]^T$ by sampling pixels at regular grid steps S.
2: Perturb cluster centers in to the lowest gradient position.
4: for each pixel do
5: Assign the pixel to the nearest cluster center based on initial grid interval S;
6: end for
7: repeat
8: for each pixel do
9: Locally search the nearby 9 cluster centers for the nearest one, then label this pixel with the nearest cluster's index.
10: end for
11: Update each cluster center based on pixel assignment and compute residual error dfxxE (L1 distance) between last and current iteration.
12: until $E \leq$ thread should (e.g. 0.2).
13: Enforce Connectivity.

Proposed algorithm

In this paper, a quadratic tree (split and merge) algorithm was used to locate and initialize the seed number and location through the image space rather than the old method where seeds distributed regularly as raws and columns. This proposed approach isolate initially the symmetry block from other ones, which generally cluster the image more uniforml than the traditional one. Examining figure 2 shows the difference between the proposed and the traditional method. It can be easily see that the region boundaries take different shapes rather than honey cell (hexagonal), which fit the edge better. Logically the implementation of the proposed method require other parameters like splitting threshold and min. block size to be separated as well as the block size to be taken into account as a seed pixel location.

(a)

(b)



(c)

(d)

(e)

Figure 2a- source image

b) superpixel image using SLIC
c) superpixel image using the proposed algorithm with threshold=.2
d) superpixel after merging process with threshold=.2
e) color segmented image.

Conclusions

The proposed algorithms provide us with better segmented image than the traditional one according to the subjective criterion (isolation of the foreground from the background), which is very clear after merging the superpixels cell (the last row of the figure). Other beneficially is the determination of seeds number determination was excluded as well as the low processing time.

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