CS554 Database Systems Project Report ***Kai Wang***

Discovery of Spatial Density Patterns in Large Scale Medical Images

Abstract

The project aims to detect regions that have significant and different density compared with its neighborhood. I summarized significant-different regions into three categories: 1) Over-Density, 2) Under-Density, 3) regions surrounded by Ridges/Ditches. The third one may capture regions surrounded with a very thin edge, either a ridge or ditch, which may be easily missed out. Significant-different region detection has many useful applications. It can be applied to detect the outbreak area of a possible epidemic where the number of disease cases is significantly larger than expected , identify crime hot-spots/cold-spots where crime rates are unusually high/low, detect anomaly regions of organs, where the density of cells is much higher/lower than its surroundings.

Specifically, this project is targeted at the whole slide image from PAIS dataset. The original data (*Figure 1*) I got is the text files exported from databases, with each line representing the boundary of a biological object such as cell, vessel, etc. The boundaries are composed of a sequence of points with the first point same to the last. Then, my goal in this setting is to detect regions that have significant-different object density.

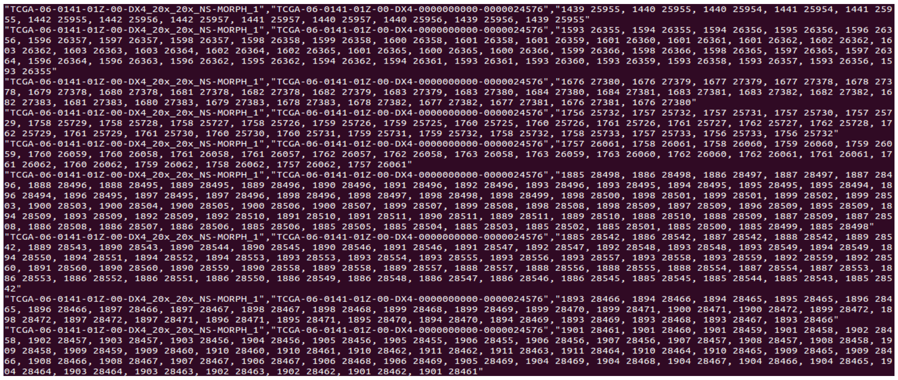

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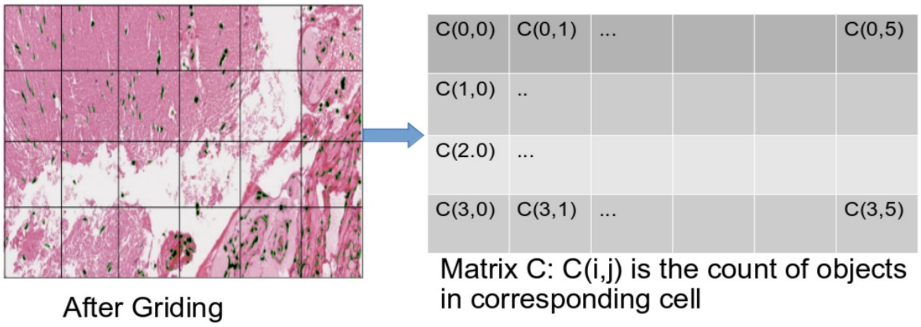
Figure 1. Dataset: Boundaries of Objects

At the beginning, the original textual object boundary dataset is partitioned into an M*N grid and transformed into a density matrix, where each entry *(i, j)* represents the count of objects inside *(i,j)th* cell. It's shown in *Figure 2*. Based on this density matrix, which is processed as an intensity image, image processing techniques such as image morphological operators and other image adjust and enhancement techniques are applied and then a region growing based algorithm is applied to extract the significant-different regions. Compared with other techniques, which only output a rough rectangular bounding box, this algorithm can return the exact shape of the significant-different regions.



C(0,0)	C(0,1)	...			C(0,5)
C(1,0)	..				
C(2.0)	...				
C(3,0)	C(3,1)	...			C(3,5)

Matrix C: C(i,j) is the count of objects in corresponding cell
After Griding

Figure 2. Intensity Matrix

Related Work

I summarized the relevant work into two groups: traditional density clustering based algorithms and grid-based algorithms.

1. Traditional Density Clustering Based Algorithms

Some density clustering based approaches for spatial objects include CLARANS, BIRCH and DBSCAN. These kind of algorithms usually have a time complexity of at least N^2, where N is the total number of objects. For my project, this is unacceptable due to the large number of objects to process. A textual file for a single tile, from which the graphs in *Figure 1* were generated, can have size near 1 GB, for example. Second, it also deviates from my goal to find the region with significant-different density statistics. It's natural to solve this problem in a more abstract and higher level.

2. Grid-based Approaches

Instead of processing the dataset directly, this category of methods first partition the space into a grid with uniform-sized cells. It computes the summarized statistics for each cell. Typically, the statistics include the total number of objects inside. But for data from different domains, for example, min, max, mean, standard deviation, etc [3], if the objects have applicable numeric attributes. Then the clustering process is based on this grid data. Grid-based approaches have the advantage of efficiency since it deals with summarized data. Actually, for my project, it can offer suitable granularity and avoid too much details and noises with a good grid size. Relevant grid-based approaches include GridScan [1], Sting [3], WaveCluster [4], continuous density queries for moving objects [5].

GridScan: The data processed in the GridScan paper [1] is a little different. It contains two kinds of points. namely case points and control points. So the definition of density is based on the ratio of case points to control points. The main idea of this method is that given a grid, it grows the current region with its neighbor cells ***c*** and merge current region with other regions if they can be connected by ***c*** and the log likelihood ***L*** of merged region is higher than ***L*** of both regions. The region growing algorithm is greedy, which means that it always tries to grow current region with the neighboring cell that maximize ***L***. Besides, it also computes the p-value to evaluate the statistical significance of extracted clusters by re-sampling.

Sting: Sting is the first work that give an insight for the grid-based spatial data mining. It uses grids on multiple levels and store summarized statistical information on each level. It's designed for answering SQL like queries and didn't actually do the clustering process.

WaveCluster: WaveCluster is a grid based approach that uses wavelet transform to extract homo-density areas. This method doesn't have any assumptions and works with any clusters of any shapes. When applying to images, it can use different filters, e.g. high-pass, low-pass filters, to extract details and remove outliers. By down-sampling after each iteration of wavelet transform, WaveCluster can achieve a clustering process at different granularity levels.

Continuous density queries for moving objects: The difference from above approaches is that this paper [5] addresses the density queries, over density and sparse density for moving objects rather than static points. Their approach applies two indexing structures, namely Quad-tree and TPR-tree to accelerate query processing. They introduced the notion of safe interval for continuous query answering, which enables dynamic maintenance of region states .

Rapid Over-density Detection: In [6][7], they introduced a rapid over-density detection method based on d-dimensional grid. Compared with the original *spatial scan statistic (Kulldorff, 1997)* that is computational infeasible for large spatial regions, the new method can achieve up to 1400x speedup and is very scalable. They built an overlap-kd tree to index the spatial regions in a hierarchical way. Compared with ordinary kd-tree, the overlap one can detect dense regions that spread over several adjacent regions. Tree pruning is applied when searching through the tree for acceleration. For each dataset, it contains two kinds of n-dimensional points, namely case point and baseline point. The ratio of count of case points to baseline points in each region is used to determine degree of over-density. Statistical importance is tested by re-sampling baseline points. The overlap technique [6,7] applied in kd-tree structure is unnecessary in region growing based approach since it can merge two splits together.

Proposed Approach: Region Growing based Algorithm

As discussed, the size of a single text file in the original dataset often in the order of hundreds of megabytes and the over-detailed information such as the boundaries of small cells is not necessary actually in this project. In fact, when we manually annotate the significant-different regions, we don't necessarily to observe the image tiles in full resolution. The objects are already like points at a suitable zoom level. Therefore, I don't consider the area of objects here, which I believe won't add more additional benefit. So, the data space is divided into a M by N grid at first, with the aggregate statistics stored for each cell in a matrix (*Figure 2*). Then a region growing based algorithm is executed to merge homogeneous neighboring cells into one big region. An advantage of region growing based method is that it can handle different cases such as over-density, under-density and regions contains ridges, at the same time. Important issues to consider for region growing include 1) selection of seed points, 2) minimum area threshold, 3) similarity threshold, etc.

Each separate text file in the dataset is composed of object boundaries inside a tile, which is often of a size around 5000 pixels in each dimension. In the griding process, the number of objects in each cell is calculated without consideration of area property. *Figure 3* is the gray image with each pixel value as the number of objects in corresponding cell. The white rectangle is the hand marked region. As we can see, the significant-different region is where the intensity of the image changes relatively great.

Description of Proposed Procedure

1. Prepare the density image:
   a) One pass through the dataset to get the maximum space ranges (max_width and max_height) of objects and the domain of x-y coordinates of all objects.
   b) Grid the whole image space with cell size (alpha*max_width, beta*max_height) and count the number of objects in each cell. Thus we get a intensity matrix with each entry equals the count of objects in corresponding cell. This part is done by the python scripts, *img.py* or

img_mark.py. The latter one also included the bounding box as in *Figure 3*.

c) Convert this matrix into gray-level image, *Figure 3*.

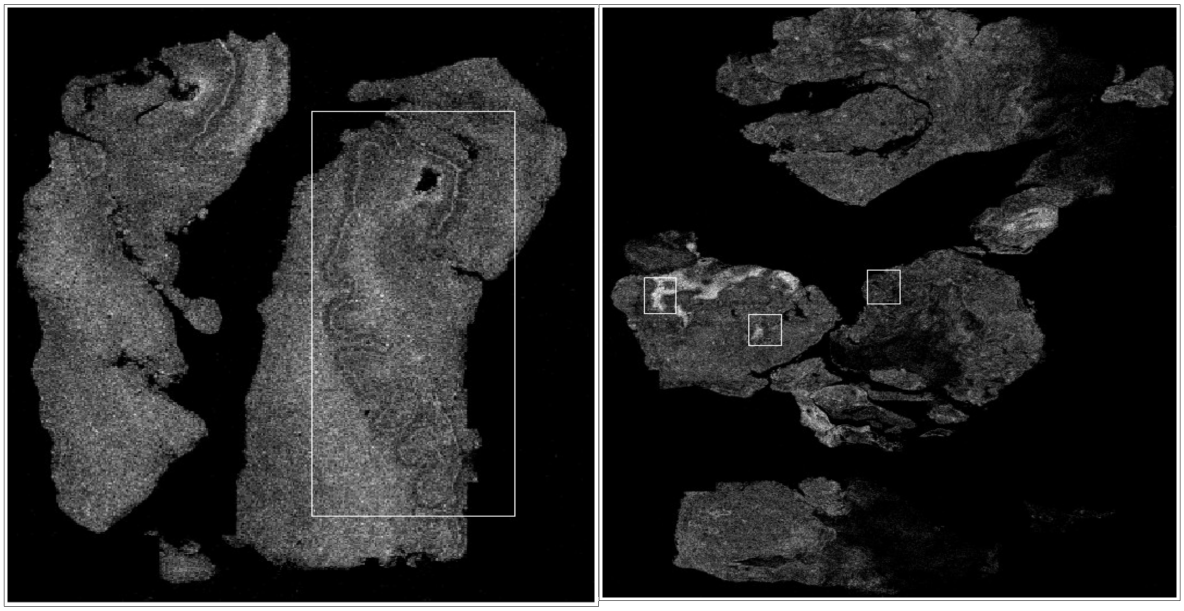


Figure 3. Example of annotated abnormal region (transformed gray image)

2. Region Growing based Detection

Code of this part is written in *Matlab*. For details of the algorithm, please refer the .m files, which have detailed documentation. Below are some issues to be considered:

a) Improve the density image:

Apply image processing techniques such as the morphological operators dilation, erosion, open, close to ***remove noises*** like very small regions and ***increase contrast*** between adjacent heterogeneous regions and ***connect separate homogeneous regions that are near to each other*** and ***smooth the image***.

Here are some useful Matlab functions I experimented with for your reference: imadjust, imdilate, imerosion, imopen, imclose, strel, histeq, brighten, strechlim, fspecial, imfilter, imreconstruction, imareaopen, imsharpen, **imfill** (remove holes), **imboundaries**, bwconncomp (neighborhood is only defined as the pixels directly ajacent, not suitable for density-based clustering), etc.

b) Rule out background and normal regions. We only want to detect the rapidly changing regions within organs rather than the edges of organs or the boundaries of normal organ regions, or the noisy fading regions. Some hints are used in a post-processing step such as average intensity values and total area of the extracted region to exclude undesirable results.

c) Hierarchical detection by down-sampling. Down-sampling with a factor ***(x,y)*** from current density image to get a more abstract image, smaller in resolution. Each pixel in the down-sampled image is the average of the x*y pixels in its corresponding rectangular region. For each down-sampled cell, calculate the statistics such as max, min, average, standard deviation as cell properties from the parent cells. These statistics vector stored in this hierarchical indexing structure are used in the region growing process. However, simple count information is proved to work great enough in experiments.

d) Seed selection. In the implementation, both automatic seed selection and interactive thresholding is provided. For the automatic seeding, seed points for region growing is selected according to the low, high thresholds parameters. Automatic threshold seeding allows users to interactively set the seed points.

e) Adaptive thresholding: Otsu's method for Adaptive Distance Threshold

Experiments

This section shows the results of results of the proposed region growing based algorithm, and watershed and hierarchical watershed or waterfall algorithm for comparison purposes.

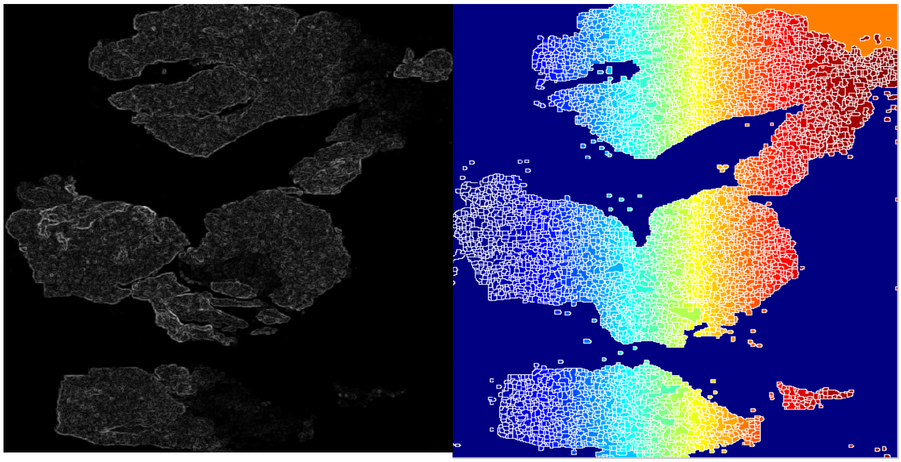


Figure 4. Over Segmentation of Watershed Algorithm

In *Figure 4*, we can see that watershed algorithm suffers a lot from over-segmentation. It cannot discriminate the over-density and under-density regions from normal organ regions. Besides, it would extract the whole organ out instead of the significant-different parts of an organ. It has no clue of the existence of the dark background. *Figure 5* shows the results of hierarchically applying the *watershed algorithm*. Based on reason just discussed, it's still unsatisfactory.

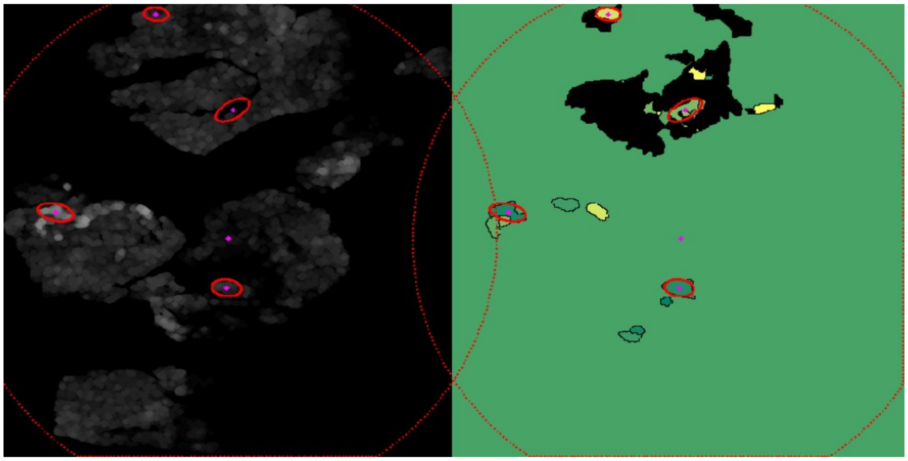


Figure 5. Hierarchical Watershed Algorithm

Results of Proposed Algorithm

The results are mainly evaluated by visual examination since hand-annotations are limited and incomplete. Some other objective measures are also available and listed in later part.

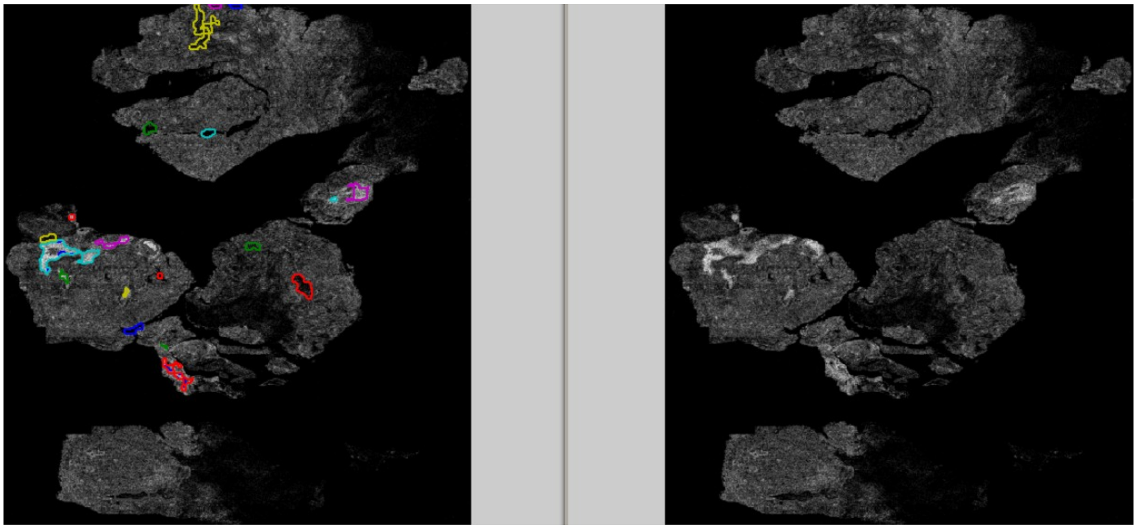


Figure 6. Sample Result 1 of proposed algorithm

Figure 6 shows great detection results of proposed region growing based algorithm. As shown, not only can it extract the much brighter regions (over-density), this approach also detected the darker holes inside the organs. Algorithm parameters are stable and easy to determine and explained in detail in source code. Better results can be achieved with simple parameter tuning.

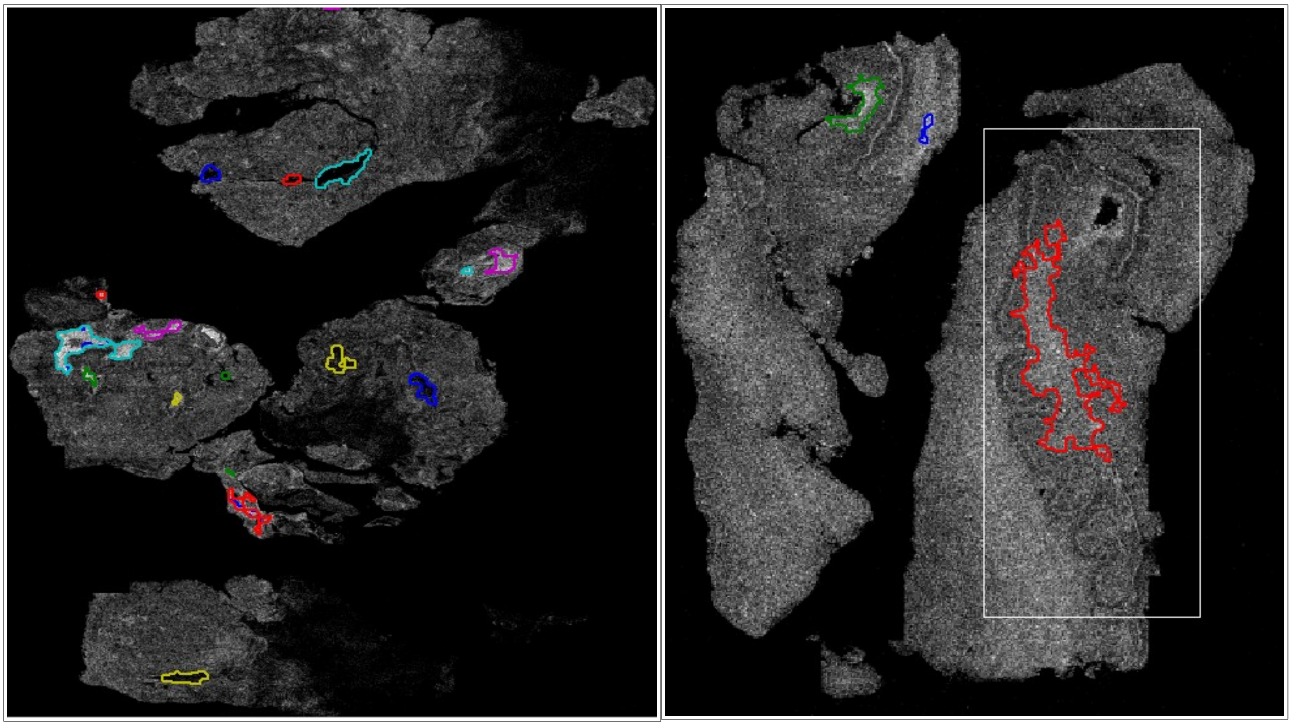


Figure 7. Sample Result 2 of proposed algorithm

In Figure 7, the left part is the result of detecting both under-density and over-density at the same time. In the right half, we can see that the amount hand-annotated regions by my classmate Dejun is very small. For each annotated picture, only a few markups are available. My algorithm not only detected the region annotated by hand, but also found other significantly brighter regions as the blue and green boundaries show. Moreover, the regions are more accurate in my algorithm, which reflects their actual shape, while the hand-annotations are only rectangles.

For users who prefer the results to be presented in forms of rectangular minimum bounding box (MMB), the output can be converted to MMB very easily.

Optional Evaluation Standards

1) Global segmentation evaluation index, Liu's F-factor [10]

$$F(I) = \sqrt{R} \times \sum e_i^2 / \sqrt{A_i}$$

2) recall rate compared with hand-annotated regions

Conclusion

The experimental results show that the proposed region growing based algorithm works great in detecting significant-different regions with efficient computational power. Different from density-based clustering algorithm, my approach construct an M*N intensity image after partitioning the original data into M*N cells. M and N is generally in the order of 10^2. Therefore, the algorithm is very fast to run and can be above 10^3 speedups. Meanwhile, the regions extracted can be any shape and reflects the real shape of the significant-different regions, rather than rough specific shapes such as rectangular bounding box or circular regions.

References

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