

An Efficient Mean Shift and Graph Based Image Segmentation

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ABSTRACT: For some applications, such as image recognition or compression, we cannot process the whole image directly for the reason that it is inefficient and unpractical. Therefore, several image segmentation algorithms were proposed to segment an image before recognition or compression. Image segmentation is to classify or cluster an image into several parts (regions) according to the feature of image, for example, the pixel value or the frequency response. Up to now, lots of image segmentation algorithms exist and be extensively applied in science and daily life. According to their segmentation method, we can approximately categorize them into region-based segmentation, data clustering, and edge-based segmentation. In this tutorial, we survey several popular image segmentation algorithms, discuss their specialties, and show their segmentation results. Moreover, some segmentation applications are described in the end.

KEYWORDS: Edge detection, Data Clustering, Mean shift Algorithm, Graph based Algorithm, Hybrid algorithm.

I. INTRODUCTION

Image segmentation is useful in many applications. It can identify the regions of interest in a scene or annotate the data. We categorize the existing segmentation algorithm into region-based segmentation, data clustering, and edge-based segmentation. Region-based segmentation includes the seeded and unseeded region growing algorithms, the JSEG, and the fast scanning algorithm. All of them expand each region pixel by pixel based on their pixel value or quantized value so that each cluster has high positional relation. For data clustering, the concept of them is based on the whole image and considers the distance between each data. The characteristic of data clustering is that each pixel of a cluster does not certainly connective. The basis method of data clustering can be divided into hierarchical and partitioned clustering. Furthermore, we show the extension of data clustering called mean shift algorithm, although this algorithm much belonging to density estimation. The last classification of segmentation is edge-based segmentation. This type of the segmentations generally applies edge detection or the concept of edge. The typical one is the watershed algorithm, but it always has the over-segmentation problem, so that the use of markers was proposed to improve the watershed algorithm by smoothing and selecting markers. Finally, we show some applications applying segmentation technique in the preprocessing.

II. REGION SPLITTING AND MERGING

The main goal of region splitting and merging is to distinguish the homogeneity of the image. Its concept is based on quad trees, which means each node of trees has four descendants and the root of the tree corresponds to the entire image. Besides, each node represents the subdivision of a node into four descendant nodes.

Let R represent the entire image region and decide a predicate P . The purpose is that if $P(R) \square \text{FALSE}$, we divide the image R into quadrants. If P is FALSE for any quadrant, we subdivide that quadrant into subquadrants, and so on. Until that, for any region R_i , $P(R_i) \square \text{TRUE}$. After the process of splitting, merging process is to merge

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two adjacent regions R_j and R_k if $P(R_j, R_k) \square TRUE$. The summarized procedure is described as follows:

- Step1. Splitting steps: For any region R_i , which $P(R_i) \square FALSE$, we split it into four disjoint quadrants.
- Step2. Merging steps: When no further splitting is possible, merge any adjacent regions R_j and R_k for which $P(R_j, R_k) \square TRUE$.
- Step3. Stop only if no further merging is possible.

We conclude the advantages and disadvantages of region splitting and merging: Advantages:

- a. The image could be split progressively according to our demanded resolution because the number of splitting level is determined by us.
- b. We could split the image using the criteria we decide, such as mean or variance of segment pixel value. In addition, the merging criteria could be different to the splitting criteria.

III. DATA CLUSTERING

Data clustering is one of methods widely applied in image segmentation and statistic. The main concept of data clustering is to use the centroid to represent each cluster and base on the similarity with the centroid of cluster to classify. According to the characteristics of clustering algorithm, we can roughly divide into “hierarchical” and “partitional” clustering. Except for this two classes, mean shift algorithm is part of data clustering, too, and its concept is based on density estimation[3]-[6].

3.1. Hierarchical Clustering

The concept of hierarchical clustering is to construct a dendrogram representing the nested grouping of patterns (for image, known as pixels) and the similarity levels at which groupings change. We can apply the two-dimensional data set to interpret the operation of the hierarchical clustering algorithm.

The hierarchical clustering can be divided into two kinds of algorithm: the hierarchical agglomerative algorithm and the hierarchical divisive algorithm. We describe the detail of two algorithms as below, respectively.

Hierarchical agglomerative algorithm:

- Step1. Set each pattern in the database as a cluster C_i and compute the proximity matrix including the distance between each pair of patterns.
- Step2. Use the proximity matrix to find out the most similar pair of clusters and then merge these two clusters into one cluster. After that, update the proximity matrix.

Notice that there are several ways to define the “distance” between each pair of patterns. The most popular definitions are the single-link and complete-link algorithms. If we assume $D(C_i, C_j)$ as the distance between cluster C_i and C_j , and assume $d(a, b)$ as the distance between pattern a and b . Then the distance definition of single-link method is

$$D(C_i, C_j) \square \min_{\substack{a \square C_i, \\ b \square C_j}} d(a, b) \tag{3.1}$$

which means the distance between two clusters is the minimum of all pairwise distances between patterns in the two clusters. The distance definition of complete-link method is

$$D(C_i, C_j) \square \max_{\substack{a \square C_i, \\ b \square C_j}} d(a, b) \tag{3.2}$$

two clusters[7].

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Hierarchical divisive algorithm:

Before we introduce the algorithm of hierarchical division, it has to define the distance between pattern x (as for image, the pixel) and cluster C as $d(x, C) =$ the mean of the distance between x and each pattern in the cluster C . The steps of hierarchical divisive algorithm are as below.

- Step1. Start with one cluster of the whole database (as for image, the whole image).
- Step2. Find the pattern x_i in cluster C_i satisfied $d(x, C_i) = \max(d(y, C_i))$, for

$\forall y \in C_i$, where $i = 1, 2, \dots, N$ and N is the current number of clusters in the whole database.

Step3. Split x_i out as a new cluster C_{i+N} , and then compute $d(y, C_i)$ and $d(y, C_{i+N})$, for $\forall y \in C_i$. If $d(y, C_i) > d(y, C_{i+N})$, then split y out of C_i and merge it into C_{i+N} .

Step4. Repeat to Step 2 until all of the clusters are not change anymore.

The advantages and disadvantages of the hierarchical algorithm are concluded as below.

IV. MEAN SHIFT SEGMENTATION

The mean shift based segmentation technique was introduced in and has become widely-used in the vision community. It is one of many techniques under the heading of “feature space analysis”. The mean shift technique is comprised of two basic steps: a mean shift filtering of the original image data (in feature space), and a subsequent clustering of the filtered data points. Below we will briefly describe each of these steps and then discuss some of the strengths and weaknesses of this method[8].

4.1 Filtering

The filtering step of the mean shift segmentation algorithm consists of analyzing the probability density function underlying the image data in feature space. Consider the feature space consisting of the original image data represented as the (x, y) location of each pixel, plus its colour in $L^*u^*v^*$ space (L, u, v) . The modes of the pdf underlying the data in this space will correspond to the locations with highest data density. In terms of a segmentation, it is intuitive that the data points close to these high density points (modes) should be clustered together. Note that these modes are also far less sensitive to outliers than the means of, say, a mixture of Gaussians would be[9]-[11].

The mean shift filtering step consists of finding the modes of the underlying pdf and associating with them any points in their basin of attraction. Unlike earlier techniques, the mean shift is a non-parametric technique and hence we will need to estimate the gradient of the pdf, $f(x)$, in an iterative manner using kernel density estimation to find the modes. For a data point x in feature space, the density gradient is estimated as being proportional to the mean shift vector:

$$\hat{\nabla}f(x) \propto \frac{\sum_{i=1}^n x_i g\left(\frac{\|x-x_i\|}{h}\right)}{\sum_{i=1}^n g\left(\frac{\|x-x_i\|}{h}\right)} - x \quad (1)$$

where x_i are the data points, x is a point in the feature space, n is the number of datapoints (pixels in the image), and g is the profile of the symmetric kernel G . We use the simple case where G is the uniform kernel with radius vector h . Thus the above equation simplifies to:

$$\hat{\nabla}f(x) \propto \left[\frac{1}{|S_{x,h}|} \sum_{x_i \in S_{x,h}} x_i \right] - x \quad (2)$$

For every data point (pixel in the original image) x we can iteratively compute the gradient estimate in Eqn. 2 and move x in that direction, until the gradient is below a threshold. Thus we have found the points where $\text{crf}(x) = 0$, the modes

of the density estimate. We can then replace the point x with x_0 , the mode with which it is associated. Finding the mode associated with each data point helps to smooth the image while preserving discontinuities. Intuitively, if two points x_i and x_j are far from each other in feature space, then $x_i \notin S_{x_j, h_s, h_r}$ and hence x_j doesn't contribute to the mean shift vector gradient estimate and the trajectory of x_i will move it away from x_j . Hence,

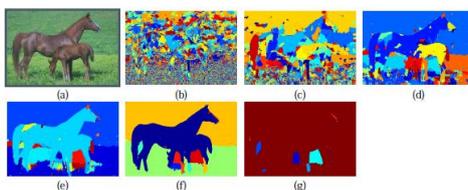


Figure 1: Example of changing scores for different segmentation granularities: (a) Original image, (b)-(g) mean shift segmentations using scale bandwidth (h_s) 7 and color bandwidths (h_r) 3, 7, 11, 15, 19 and 23 respectively.

pixels on either side of a strong discontinuity will not attract each other. However, filtering alone does not provide a segmentation as the modes found are noisy. This “noise” stems from two sources. First, the mode estimation is an iterative process, hence it only converges to within the threshold provided (and with some numerical error). Second, consider an area in feature space larger than S_{x_j, h_s, h_r} and where the colour features are uniform or have a gradient of 1. Since the pixel coordinates are uniform by design, the mean shift vector will be 0 in this region, and the data points will not move and hence not converge to a single mode. Intuitively, however, we would like all of these datapoints to belong to the same cluster in the final segmentation. For these reasons, mean shift filtering is only a preprocessing step, and a second step is required in the segmentation process: clustering of the filtered data points $\{x_0\}$.

Clustering

After mean shift filtering, each data point in the feature space has been replaced by its corresponding mode. As described above, some points may have collapsed to the same mode, but many have not despite the fact that they may be less than one kernel radius apart. In the original mean shift segmentation paper [1], clustering is described as a simple post-processing step in which any modes that are less than one kernel radius apart are grouped together and their basins of attraction are merged. This suggests using single linkage clustering, which effectively converts the filtered points into a segmentation.

The only other paper using mean shift segmentation that speaks directly to the clustering is [2]. In this approach, a region adjacency graph (RAG) is created to hierarchically cluster the modes. Also, edge information from an edge detector is combined with the colour information to better guide the clustering. This is the method used in the publicly available EDISON system, also described in [2]. The EDISON system is the implementation we use here as our mean shift segmentation system [12].

Discussion

Mean shift filtering using either single linkage clustering or edge-directed clustering produces segmentations that correspond well to human perception. However, as we discuss in the experiments section, this algorithm is quite sensitive to its parameters. The mean shift filtering stage has two parameters corresponding to the bandwidths (radii of the kernel) for the spatial (h_s) and colour (h_r) features. Slight variations in h_r can cause large changes in the granularity of the segmentation, as shown in Fig. 1. By adjusting the colour bandwidth we can produce over-segmentations as in Fig. 1b which show every minute detail, to reasonably intuitive segmentations as in Fig. 1f which delineate objects or large patches, to under-segmentations as in Fig. 1g which obscure the important elements completely. This issue is a major stumbling block with respect to using mean shift segmentation as a reliable preprocessing step for other algorithms, such as object recognition. For an object recognition system to actually use a segmentation algorithm, it requires that the segmentations produced be fairly stable under

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parameter changes and that the same parameters produce stable results for different images, thus easing the burden of parameter tuning. In an attempt to improve stability, we consider a second algorithm.

Efficient Graph-based segmentation

Efficient graph-based image segmentation, introduced in [4], is another method of performing clustering in feature space. This method works directly on the data points in feature space, without first performing a filtering step, and uses a variation on single linkage clustering. The key to the success of this method is adaptive thresholding. To perform traditional single linkage clustering, a minimum spanning tree of the data points is first generated (using Kruskal's algorithm), from which any edges with length greater than a given hard threshold are removed. The connected components become the clusters in the segmentation. The method in [4] eliminates the need for a hard threshold, instead replacing it with a data-dependent term.

More specifically, let $G = (V, E)$ be a (fully connected) graph, with m edges and n vertices. Each vertex is a pixel, x , represented in the feature space. The final segmentation will be $S = (C_1, \dots, C_r)$ where C_i is a cluster of data points. The algorithm is:

1. Sort $E = (e_1, \dots, e_m)$ such that $|e_t| \leq |e_{t'}| \forall t < t'$
2. Let $S^0 = (\{x_1\}, \dots, \{x_n\})$, in other words each initial cluster contains exactly one vertex.
3. For $t = 1, \dots, m$
 - (a) Let x_i and x_j be the vertices connected by e_t .
 - (b) Let $C_{x_i}^{t-1}$ be the connected component containing point x_i on iteration $t-1$, and $l_i = \max_{x_j \in C_{x_i}^{t-1}} |e_{x_i x_j}|$ be the longest edge in the minimum spanning tree of $C_{x_i}^{t-1}$. Likewise for l_j .
 - (c) Merge $C_{x_i}^{t-1}$ and $C_{x_j}^{t-1}$ if

$$|e_t| < \min\left\{l_i + \frac{k}{|C_{x_i}^{t-1}|}, l_j + \frac{k}{|C_{x_j}^{t-1}|}\right\} \quad (3)$$

where k is a constant.

4. $S = S^m$

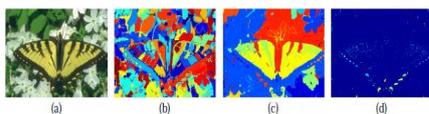


Figure 2: Example of changing scores for different parameters using efficient graph-based segmentation: (a) Original image. (b)-(d) efficient graph-based segmentations using scale bandwidth (h_s) 7, color bandwidth (h_c) 7 and k values 5, 25, 125 respectively.

We can make the algorithm more efficient by considering only the 100 shortest edges from any vertex instead of the fully connected graph. This does not result in any perceptible quality loss. In contrast to single linkage clustering which uses a constant K to set the threshold on edge length for merging two components in Eqn. 3, efficient graph-based segmentation uses a variable threshold. This threshold effectively allows two components to be merged if the minimum edge connecting them does not have length greater than the maximum edge in either of the components' minimum spanning trees, plus a term $= k|C_t - 1| x_i |$. As defined here, $_{}$ is dependent on a constant k and the size of the component [13].

V. HYBRID SEGMENTATION ALGORITHM

An obvious question emerges when describing the mean shift based segmentation method [1] and the efficient graph based clustering method [4]: can we combine the two methods to give better results than either method alone? More specifically, can we combine the two methods to create more stable segmentations that are less sensitive to parameter

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changes and for which the same parameters give reasonable segmentations across multiple images? In an attempt to answer these questions, the third algorithm we consider is a combination of the previous two algorithms: first we apply mean shift filtering, and then we use efficient graph-based clustering to give the final segmentation.

The result of applying this algorithm with different parameters can be seen in Fig.3. Notice that for $hr = 15$ the quality of the segmentation is high. Also notice that the rate of granularity change is slower than either of the previous two algorithms, even

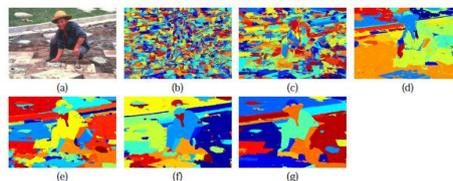


Figure 3: Example of changing scores for different parameters using a hybrid segmentation algorithm which first performs mean shift filtering and then efficient graph-based segmentation: (a) Original image, (b)-(g) segmentations using scale bandwidth (h_s) 7, and color bandwidth (h_c) and k value combinations (3,5), (3,25), (3,125), (15,5), (15,25), (15,125) respectively.

VI.COMPARISONS

Now that we have described the algorithms we wish to compare, and a measure for comparison, we can finally describe the specific comparisons we wish to perform. We believe that there are two key factors which allow for the use of a segmentation algorithm in a larger object detection system: correctness and stability.

Correctness is the obvious ability that we desire from any algorithm, the ability to produce results that are consistent with ground truth. Thus correctness is measured by the size of the NPR index. It has been often argued that the correctness of a segmentation is irrelevant, with the only relevant fact being whether or not the segmentation improves the recognition system. If the recognition system to be used is known, then it may be appropriate to measure the performance of the segmentation algorithm in conjunction with the rest of the system. However, there is value in weeding out potential segmentation algorithms which may give non-sensical results, and this can be done separately from the rest of the system. Also, it is often the case that it is not known beforehand which recognition algorithm will be best suited to a given problem, hence it is useful to have a generally well-behaved segmentation algorithm to use with multiple recognition algorithms. In addition, when evaluating a system with multiple components, it is often important to know which component specifically is causing a certain behavior. Thus, we present here a comparison of the correctness of the segmentation algorithms apart from any recognition system. Perhaps a more important indication of a segmentation algorithm's usefulness is its stability. If an algorithm gives reasonably correct segmentations on average, but

is wildly unpredictable on any given image or with any given parameter set, it will be useless as a preprocessing step. We would like a preprocessing step to produce consistently correct segmentations of similar granularity so that any system built on top of it can predict its outcome. We require segmentations with low bias and low variance. There are two basic types of stability, stability with respect to parameters and stability across images. Stability with respect to parameters refers to achieving consistent results on the same image given different parameter inputs to the algorithm. In other words, we would like the algorithm to have low variability with respect to its parameters. Stability across images refers to achieving consistent results on different images given the same set of parameters. If a segmentation algorithm can be shown to be both correct and stable, then it will be a useful preprocessing step for many systems.

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VII. EXPERIMENTS

The following plots explore each of the issues raised in the previous section. Note that the axes for each kind of plot have been kept constant so plots may be compared easily. In each experiment, the label 'EDISON' refers to the publicly available EDISON system for mean shift segmentation [2], the label 'FH' refers to



Figure 6: Examples of images from the Berkeley image segmentation database [5]

the efficient graph-based segmentation method by Felzenszwalb and Huttenlocher [4], and the label 'MS+FH' refers to our hybrid algorithm of mean shift filtering followed by efficient graph-based segmentation. All of the experiments were performed on the publicly available Berkeley image segmentation database [5], which contains 300 images of natural scenes with approximately five to seven hand segmentations of each image as ground truth. Examples of the images are shown in Fig. 6. In all of the following plots we have fixed the spatial bandwidth $h_s = 7$, since it seems to be the least sensitive parameter and removing it makes the comparison more approachable. Also, although the FH algorithm as defined previously only had one parameter, k , we need to add two more. The FH algorithm requires the computation of the distances between points in feature space. Since our feature space consists of $\{x, y, L, u, v\}$, we need to put all of the dimensions into the same scale. Hence we will divide each dimension by the corresponding $\{h_s, h_r\}$ as in the EDISON system.

So each algorithm was run with a parameter combination from the sets: $h_s = 7$, $h_r = \{3, 7, 11, 15, 19, 23\}$, and $k = \{5, 25, 50, 75, 100, 125\}$.

VIII. CONCLUSION

In this paper we have proposed a framework for comparing image segmentation algorithms, and performed one such comparison. Our framework consists of comparing the performance of segmentation algorithms based on three important characteristics: correctness, stability with respect to parameter choice, and stability with respect to image choice. If an algorithm performs well with respect to all of these characteristics, it has the potential to be useful as part of a larger vision system. The measure used within our framework is the Normalized Probabilistic Rand index, which facilitates principled comparisons between segmentations of the same or different images, and generated with multiple algorithms and parameters. The NPR index does not place any restrictions on the number or distribution of regions in competing segmentations, and it generates scores which are easily interpretable, making it ideal for this task.

REFERENCES

1. D. Comaniciu, P. Meer, "Mean shift: A robust approach toward feature space analysis", IEEE Trans. on Pattern Analysis and Machine Intelligence, 2002, 24, pp. 603-619

DOI: 10.15680/IJIRSET.2014.0312122

International Journal of Innovative Research in Science, Engineering and Technology

(An ISO 3297: 2007 Certified Organization)

Vol. 3, Issue 12, December 2014

2. Udayakumar R., Khanaa V., Kaliyamurthie K.P., "High data rate for coherent optical wired communication using DSP", Indian Journal of Science and Technology, ISSN : 0974-6846, 6(S6) (2013) 4772-4776.
3. C. Christoudias, B. Georgescu, P. Meer, "Synergism in Low Level Vision", Intl Conf on Pattern Recognition, 2002, 4, pp. 40190
4. Selva Kumar S., Ram Krishna Rao M., Deepak Kumar R., Panwar S., Prasad C.S., "Biocontrol by plant growth promoting rhizobacteria against black scurf and stem canker disease of potato caused by Rhizoctonia solani", Archives of Phytopathology and Plant Protection, ISSN : 0323-5408, 46(4) (2013) pp.487-502.
5. B. Georgescu, I. Shimshoni, P. Meer, "Mean Shift Based Clustering in High Dimensions: A Texture Classification Example", Intl Conf on Computer Vision, 2003
6. Udayakumar R., Khanaa V., Kaliyamurthie K.P., "Optical ring architecture performance evaluation using ordinary receiver", Indian Journal of Science and Technology, ISSN : 0974-6846, 6(S6) (2013) pp. 4742-4747.
7. D. Martin, C. Fowlkes, D. Tal, J. Malik, "A Database of Human Segmented Natural Images and its Application to Evaluating Segmentation Algorithms and Measuring Ecological Statistics", Intl Conf on Computer Vision, 2001.
8. Subha Palaneeswari M., Abraham Sam Rajan P.M., Silambanan S., Jothimalar, "Blood lead in end-stage renal disease (ESRD) patients who were on maintenance haemodialysis", Journal of Clinical and Diagnostic Research, ISSN : 0973 - 709X, 6(10) (2012) pp.1633-1635.
9. R. Unnikrishnan, C. Pantofaru, M. Hebert, "A Measure for Objective Evaluation of Image Segmentation Algorithms", CVPR workshop on Empirical Evaluation Methods in Computer Vision, 2005.
10. Udayakumar R., Khanaa V., Kaliyamurthie K.P., "Performance analysis of resilient fth architecture with protection mechanism", Indian Journal of Science and Technology, ISSN : 0974-6846, 6(S6) (2013) pp. 4737-4741
11. R. Unnikrishnan, M. Hebert, "Measures of Similarity", IEEE Workshop on Computer Vision Applications, 2005, pp. 394-400.
12. D. Verma, M. Meila, "A comparison of spectral clustering algorithms", University of Washington technical report, 2001.
13. R. Kannan, S. Vempala, A. Vetta, "On clusterings - good, bad and spectral", FOCS, 2000, pp. 367-377.
14. T.Nalini ,A.Gayathri,HVS Based Enhanced Medical Image Fusion ,International Journal of Innovative Research in Computer and Communication Engineering,ISSN (Print) : 2320 – 9798 , pp 170-173, Vol. 1, Issue 2, April 2013.
15. S.Thirunavukkarasu, r.K.P.Kaliyamurthie ,EFFICIENT ALLOCATION OF DYNAMICRESOURCES IN A CLOUD,International Journal of Innovative Research in Computer and Communication Engineering, ISSN: 2249-2651, pp 24-29,Volume1 Issue3 Number2–Dec2011
16. K.G.S. VENKATESAN,Planning in FARS by dynamic multipath Reconfiguration system failure recovery in Wireless Mesh Network,International Journal of Innovative Research in Computer and Communication Engineering,ISSN(Online): 2320-9801,pp 5304-5312,Vol. 2, Issue 8, August 2014.
17. G.Michael, An Empirical Approach – Distributed Mobility Management for Target Tracking in MANETs ,International Journal of Innovative Research in Computer and Communication Engineering , ISSN (Print) : 2320 – 9798 , pp 789-794 , Vol. 1, Issue 4, June 2013.
18. G.AYYAPAN , Malicious Packet Loss during Routing Misbehavior - Identification, International Journal of Innovative Research in Computer and Communication Engineering, ISSN(Online): 2320-9801, pp 4610-4613 ,Vol. 2, Issue 6, June 2014