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Image Segmentation and Classification- A Review

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Abstract: Segmentation is nothing but making the part of image or any object. Pattern recognition and image analysis are the initial steps of image segmentation. These segmented regions are classified on the basis of a variety of features derived from the classical Gestalt cues, including contour, texture, brightness and good continuation. Image segmentation is most of judging or analyzing function in image processing and analysis. Image segmentation refers to partition of an image into different regions that are homogeneous or similar and inhomogeneous in some characteristics. In a preprocessing stage an image is oversegmented into superpixels by normalized cut algorithm. Using the different algorithms the current methodologies of image segmentation is reviewed so that user interaction is possible for images. Methods of image analysis belong to a general interdisciplinary area of multidimensional signal processing.

Keywords: Classification, Image, Oversegmented, Pixels, Preprocessing, Segmentation

I. INTRODUCTION

Many researchers have studied the image segmentation in the 80's mainly, then, this area has been neglected at the expense of intensity images due to their easy acquisition. During the past decade, with the influx of 3D geometric representations and their complex geometric representations, a different interest was focused on image segmentation and classification [6]. Image segmentation in general is defined as a process of partitioning an image into homogeneous groups such that each region is homogeneous but the union of no two adjacent regions is homogeneous. Efficient image segmentation is one of the most critical tasks in automatic image processing. We formulate the computational problem of segmentation as a classification between “good” segmentations and “bad” segmentations. How do we distinguish good segmentations from bad segmentations? The criterion of”good” segmentation is not easily defined because it is subjective by nature [5]. Classical Gestalt theory has developed various principles of grouping such as proximity, similarity and good continuation. The principle of good continuation states that a good segmentation should have smooth boundaries. The principle of similarity is twofold:

1. Intra-region similarity: the elements in a region are similar. This includes similar brightness, similar texture, and low contour energy inside the region;
2. Inter-region (dis)similarity: the elements in different regions are dissimilar. This in turn includes dissimilar brightness, dissimilar texture, and high contour energy on region boundaries [1,2].

Image segmentation is the most critical functions in image analysis and processing. Fundamentally segmentation results affect all the subsequent processes of image analysis such as object representation and description. Medical images play vital role in assisting health care providers to access patients for diagnosis and treatment. Studying medical images depends mainly on the visual interpretation of the radiologists. This visual interpretation involves the use of several image segmentation and classifications techniques.[18]

The outline of the paper is as follows.

In 2 we introduce a preprocessing stage which organizes an image into "superpixels”. Section 3 describes categorization of segmentation techniques. In 4, we define a set of features for segments, including Gestalt cues of contour, texture, brightness and good continuation. Based on this model for segments, in 5 problem of finding the best segmentation is discussed. space of segmentations. The experimental results are discussed in 6 and 7 concludes the paper.

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II. OVERSEGMENTATION AS PREPROCESSING

In this section we present a preprocessing stage to group pixels into "superpixels". The motivations of this preliminary grouping are: (1) pixels are not natural entities; they are merely a consequence of the discrete representation of images; and (2) the number of pixels is high even at moderate resolutions; this makes optimization on the level of pixels intractable. We would like to work with "superpixels' which are local, coherent, and which preserve most of the structure necessary for segmentation at the scale of interest. We apply the Normalized Cuts algorithm [5, 8] to produce the superpixel map. Both contour and texture cues are used. The affinity matrix has local connections only. Figure 1 shows an example of the oversegmentation with the number of superpixels.

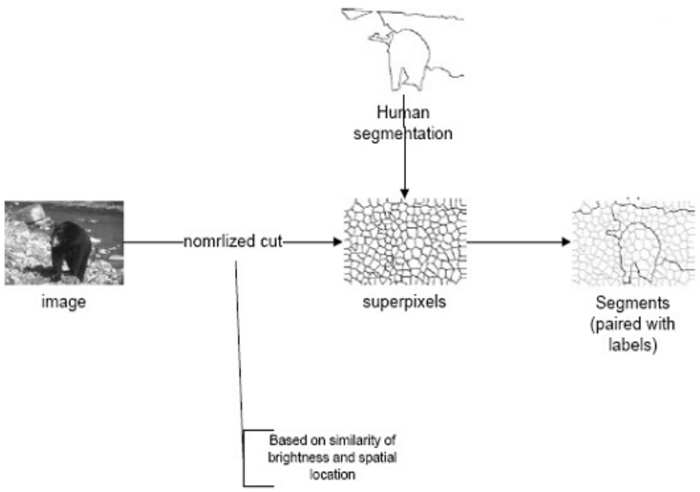

Fig 1: Roadmap of Training Phase

Normalized Cut

As a preprocessing step, we oversegment an image into superpixels using normalized cut (as shown in figure 1). The segmentation problem in this step is treated as a graph partitioning problem[5]. The algorithm exploits the hierarchical nature of partitioning, and is recursively applied to the segmented portion until the segment meets a certain threshold condition. We observe from this example that the superpixels are roughly homogeneous in size and shape; this fact simplifies the computation in later stages.

III. CLASSIFICATION OF SEGMENTATION TECHNIQUES

Image segmentation can be broadly classified into two types:
1. Local segmentation
2. Global segmentation

Global segmentation is concerned with segmenting a whole image. Global segmentation deals mostly with segments consisting of relatively large number of pixels[10, 11]. This makes estimated parameter values for global segments most robust.

Image segmentation can be approach from three different philosophical perspectives. They are as region approach, boundary approach and edge approach as illustrated in figure.

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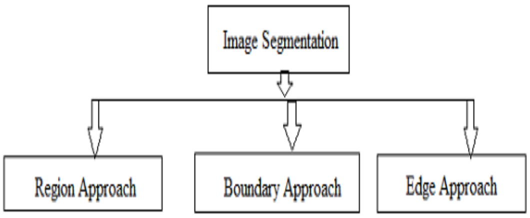

Figure 2. Image Segmentation Approach

If the pixel belongs to object, it has value one, otherwise it is zero. Segmentation [12] is the operating at the threshold between low-level image processing and image analysis. After the complete procedure of segmentation, the pixel belongs to the object.

- •Structural Techniques
- •Stochastic Techniques
- •Hybrid Techniques

Structural Techniques[13] use some information about the structure of the region for segmentation. Stochastic techniques are applied on discrete pixels without knowing or considering any structural information of the region. Statistical analysis is one of the techniques on which the stochastic technique [13] is based. Hybrid technique [13] include those techniques which possess the characteristics of both structural and stochastic techniques.

IV. WHAT IS A GOOD SEGMENT?

Segmentation is a collection of segments. To answer the question "What is a good segmentation?" we need to answer "What is a good segment?" first. In this section, we will define a set of features for segments, evaluate the usefulness of these features, and train a classifier from them.

Features for grouping

For static images, the classical Gestalt principles of grouping include proximity, similarity, good continuation (curvilinear continuity), closure as well as symmetry and parallelism. In our model, for a segment [14,15] we define the following features:

1. Inter-region texture similarity
2. intra-region texture similarity
3. Inter-region brightness similarity
4. intra-region brightness similarity
5. Inter-region contour energy
6. intra-region contour energy
7. Curvilinear continuity

V. FINDING GOOD SEGMENTATIONS

"What is a good segmentation?" We make the simplifying assumption that the "goodness" of the segments *S* in a segmentation *S* are independent. [16] The problem of finding the best segmentation becomes the optimization of *f* in the space of all segmentations. The objective *f* is simple in form but the search space of all segmentations is large. Following the Markov Chain Monte Carlo paradigm [17], we adopt a simple strategy of random search based on simulated annealing. The dynamics in this random search involves three basic moves: (1) shift: a superpixel is shifted from its segment to an adjacent segment; (2) merge: two adjacent segments are merged into one; and (3) split: a segment is split into two. The first two moves are straightforward. For splitting a segment, we use a simple method by clustering the superpixels in the segment based on location and mean intensity. This clustering is also used to initialize the search. At each step, the algorithm randomly picks one of the moves above and construct a new segmentation *S'*.

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VI. CONCLUSION

In this paper we have presented a discriminative frame-work for segmentation as the classification of "good" segmentations and "bad" segmentations. As a preprocessing step, we oversegmented the image into fixed number of superpixels using normalized cut [5]. We defined two features of segment that represent the similarity within a segment and dissimilarity between segments respectively. The dataset for training the classifier is generated by using human marked segmentation. Positive data was generated by matching the corresponding segment produced by merging superpixels to the correct image. Negative data was generated by matching them to randomly picked image. In the testing phase, we defined an objective function to find the best segmentation. This objective function has additional term to keep our algorithm from failing [8]. Our classifier is not perfect for a few reasons. The most obvious one is that we only considered brightness as determining features. Real world images have other important properties like texture and curvilinear continuity, etc. Once one find a way to formulate these features, these can be immediately handled in our framework as the same way the brightness is. That is, we can define two features for each property which are corresponding to intra-region similarity and inter-region dissimilarity, respectively. We can also include global features such as symmetry or object model to improve the performance.

REFERENCES

[1] X. Ren & J. Malik, "Learning a Classification Model for Segmentation", ICCV '03 volume 1, pages 10-17, 2003.

[2] D. Martin, C. Fowlkes, J. Malik, "A database of human segmented natural images and its application to evaluating segmentation algorithms and measuring ecological statistics", ICCV '01 , volume2, pages 416-423, 2001.

[3] J. Shi and J. Malik, "Normalized cuts and image segmentation", IEEE Trans. Pattern Analysis and Machine Intelligence, 22(8):888–905, August 2000.

[4] P. Karch, I. Zolotova, "An Experimental Comparison of Modern Methods of Segmentation", IEEE 8th International Symposium on SAMI, pp. 247-252, 2010.

[5] J. Shi and J. Malik, "Normalized cuts and image segmentation." CVPR '97, pages 731–7, 1997.

[6] M. Nixon and A. Aguado, " Feature Extraction & Image Processing" NewNes Elsevier, 2004.

[7] J. Puzicha, T. Hofmann, and J. Buhmann, " Non-parametricsimilarity measures for unsupervised texture segmentationand image retrieval" CVPR '97, pages 267–272, 1997.

[8] J. Malik, S. Belongie, T. Leung, and J. Shi, "Contour and texture analysis for image segmentation" Int'l. Journal of Computer Vision, 43(1):7–27, June 2001.

[9] Hanzi Wang, David Suter, "MDPE: A Very Robust Estimator for Model Fitting and Range Image Segmentation" Department of Electrical and Computer Systems Engineering, Monash University, Vol. 9, Issue 4, No 1, July 2012

[10] Jesmin F. Khan, Sharif M. A. Bhuiyan, and Reza R. Adhami, "Image Segmentation and Shape Analysis for Road-Sign Detection", IEEE Transactions on Intelligent Transportation systems, VOL. 12, NO. 1, MARCH 2011

[11] Andrew Janowczyk, Sharat Chandran, Rajendra Singh, Dimitra Sasaroli, George Coukos, Michael D. Feldman, and Anant Madabhushi, "High-Throughput Biomarker Segmentation on Ovarian Cancer Tissue Microarrays via Hierarchical Normalized Cuts", IEEE Transactions on Biomedical Engineering, VOL. 59, NO. 5, MAY 2012

[12] K. K. Singh, A. Singh, "A Study of Image Segmentation Algorithms for Different Types of Images", International Journal of Computer Science Issues, Vol. 7, Issue 5, 2010

[13] Wahba Marian, "An Automated Modified Region Growing Technique for Prostate Segmentation in Trans-Rectal Ultrasound Images, Master's Thesis", Department of Electrical and Computer Engineering, University of Waterloo, Waterloo, Ontario, Canada, 2008.

[14] X. Ren and J. Malik, "A probabilistic multi-scale model forcontour completion based on image statistics", ECCV '02,volume 1, pages 312–327, 2002.

[15] J. Malik, S. Belongie, T. Leung, and J. Shi, "Contour and texture analysis for image segmentation", Int'l. Journal of Computer Vision, 43(1):7–27, June 2001.

[16] Z. Tu, S. Zhu, and H. Shum, " Image segmentation by datadriven markov chain monte carlo", ICCV '01, volume 2,pages 131–138, 2001.

[17] C. Fowlkes, D. Martin, and J. Malik, "Learning affinity functions for image segmentation: combining patch-based and gradient-based approaches", CVPR '03, volume 2, pages54–61, 2003.

[18] Dinesh D. Patil1, Sonal G. Deore, "Medical Image Segmentation", IJCSMC, Vol. 2, Issue. 1, January 2013, pg.22 – 27