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A New Method for Image Segmentation

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Abstract - Image processing is a form of signal processing. One of the typical operations on image processing is image segmentation. In this paper, we use new image segmentation algorithms based on information bottleneck method. Here we are going to use three algorithms; first we introduce the split-and-merge algorithm, where an image is segmented into set of regions (input) and the intensity histogram bins (output) is obtained. The second algorithm is the histogram clustering algorithm, where the input variable represents the histogram bins and the output is given by the set of regions. Finally, the registration based segmentation for two registered multimodal images. Image registration is the process of overlaying images (two or more) of the same scene taken at different times, from different viewpoints, and/or by different sensors. The registration geometrically aligns two images (the reference and sensed images).

Index Terms -- Image Segmentation, Image Registration, Quad tree, Clustering, Information Bottleneck Method

1. INTRODUCTION

Image segmentation is to cluster pixels into Salient image regions, i.e., regions corresponding to individual surfaces, Objects, or natural parts of objects. Segmentation could be used for object recognition, occlusion boundary estimation within motion or stereo systems, image compression, image editing, or image database look-up. A new method for unsupervised image category clustering is presented, based on a Continuous version of a recently introduced information theoretic principle, the information Bottleneck (IB). The clustering method is based on hierarchical grouping: Utilizing a Gaussian Mixture model, each image in a given archive is first represented as a set of coherent regions in a selected feature space. Images are next grouped such that the mutual information between the clusters and the image content is maximally preserved. The appropriate number of clusters can be determined directly from the IB principle. Experimental results that demonstrate the performance of the proposed clustering method on a real image database. There are two essential issues in a region-merging algorithm: order of merging and the stopping criterion. In the proposed algorithm, these two issues are solved by a novel predicate, which is defined by the sequential probability ratio test and the minimal cost criterion. Starting from an over segmented image, neighboring regions are progressively merged if there is an evidence for merging according to this predicate. We show that the merging order follows the principle of dynamic programming. This formulates the image segmentation as an inference problem, where the final segmentation is established based on the observed image.

The following methods represent the main contribution of this paper.

- *Quad tree decomposition.*

An image can be represented by a data structure known as the quad-tree [7] [9] [14]. A quad tree is a tree whose nodes either leaves or with 4 children. To represent an image by a quad-tree representation, the image is first divided into 4 quadrants of equal size. Then, each quadrant will be further sub-divided if it has more than one color.

- *Recursive Thresholding*.

It exploits region statistics to controls partitioning. The entire image is first split, and then each extracted region is considered for further splitting. Each successive split improves the context in which additional decisions are made.

- *Recursive Partitioning.*

Its more general term for the repeated splitting of regions. It includes recursive thresholding, but may also exploit cluster analysis, pixel classification, and linear feature extraction. It is particularly useful because it generates a series of meaningful intermediates as it works toward a full scene parse. A disadvantage of recursive splitting is that may take long time to reach the level of small targets in a large image. Targets with distinctive spectral values can be located in one classification or thresholdig, but objects similar to the background statistics must be found by successively paring away other regions.

- *Region Split-and-Merge segments.*

Its partition an image into quasi-homogeneous Regions using a binary space partition (BSP) or a quad tree partition. In the second phase, a bottom-up strategy is used to merge the regions whose histograms are more similar

- *Histogram Clustering*

It's often used to select region centers that are
then grown, tentative regions found by over segmenting are clustered in a spectral space to find a final set of regions. I use clustering only for splitting regions, with connected component analysis, region merging, and perhaps further splitting used to verify and improve the segmentation.

- *Registration based segmentation.*

Two different algorithms are presented. The first one segments just one image at a time, while the second one segments both simultaneously. The clustering process works by extracting from each image the structures that are more relevant to the other one. In these algorithms, each image is used to control the quality of the segmentation of the other.

2. RELATED WORK

Quadrilateral-based framework for image segmentation, in which quadrilaterals are first constructed from an edge map, where neighboring quadrilaterals with similar features of interest are then merged together to form regions. Under the proposed framework, the quadrilaterals enable the elimination of local variations and unnecessary details for merging from which each segmented region is accurately and completely described by a set of quadrilaterals. To illustrate the effectiveness of the proposed framework, we derived an efficient and high-performance parameter less quadrilateral-based segmentation algorithm from the framework. The proposed algorithm shows that the regions obtained under the framework are segmented into multiple levels of quadrilaterals that accurately represent the regions without severely over or under segmenting them. When evaluated objectively and subjectively, the proposed algorithm performs better than three other segmentation techniques, namely, seeded region growing, K--means clustering and constrained gravitational clustering, and offers an efficient description of the segmented objects conducive to content-based applications.

Information Theoretic Co-clustering:

Two-dimensional contingency or co-occurrence tables arise frequently in important applications such as text, web-log and market-basket data analysis. A basic problem in contingency table analysis is co-clustering: simultaneous clustering of the rows and columns. A novel theoretical formulation views the contingency table as an empirical joint probability distribution of two discrete random variables and poses the co-clustering problem as an optimization problem in information theory — the optimal co-clustering maximizes the mutual information between the clustered random variables subject to constraints on the number of row and column clusters. We present an innovative co-clustering algorithm that monotonically increases the preserved mutual information by intertwining both the row and column clustering at all stages. Using the practical example of simultaneous word-document clustering, we demonstrate that our algorithm works well in practice, especially in the presence of sacristy and high-dimensionality.

Registration-Based Segmentation Using the Information Bottleneck Method:

In this paper we present two new clustering algorithms for medical image segmentation based on the multimodal image registration and the information bottleneck method. In these algorithms, the histogram bins of two registered multimodal 3D-images are clustered by minimizing the loss of mutual information between them. Thus, the clustering of histogram bins is driven by the preservation of the shared information between the images, extracting from each image the structures that are more relevant to the other one. In the first algorithm, we segment only one image at a time, while in the second both images are simultaneously segmented. Experiments show the good behavior of the presented algorithms, especially the simultaneous clustering.

3. PROPOSED WORK

3.1 System Architecture

The system architecture consists of an image as the input and the image undergoes the process of image analysis. Then the splitting and the merging process take place i.e., we have partitioned the image and calculated the similar histogram bins. The second module is the histogram clustering algorithm which is used to segment the relevant histogram bins. Finally we have to take two different images and calculate the mutual information by applying the above algorithm the split and merge algorithm and histogram clustering algorithm for both the images.

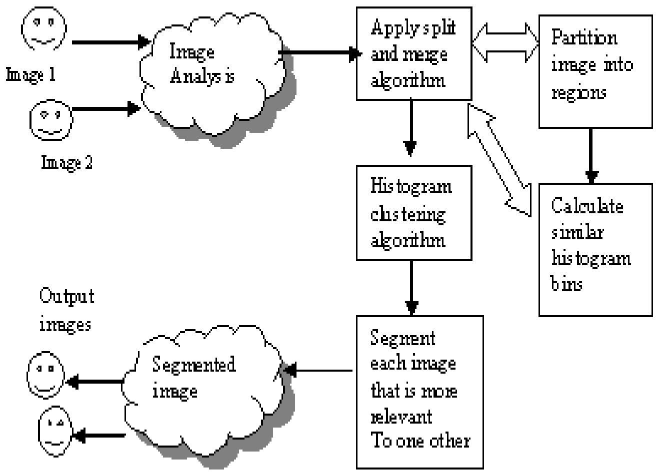

Fig.1. – System Architecture

3.2 Proposed Image segmentation Method

The problem of separating object from the background in a given image is considered. Hence, the problem boils down to determining the threshold using histogram of the given image. Often, in practice, the histograms do not show two clearly separated classes rather overlapping classes. Many methods have been suggested in the past for such kind of problem but still for overlapping classes, it is hard to determine a global threshold. Hence, attempts have been made by proposing a new approach to determine the global threshold for image segmentation by Genetic algorithm. The algorithm is found to produce satisfactory results for images having histograms with bimodal feature. Currently, attempts are made to address two class images with noises and images requiring multiple thresholds. The method provides the following steps:

4. EXPERIMENTAL RESULTS

4.1. Quad tree Decomposition

To represent an image by a quad-tree representation, the image is first divided into 4 quadrants of equal size. Then, each quadrant will be further sub-divided if it has more than one color. The process continues until each quadrant or sub quadrant (possibly a single pixel) contains only one color. In terms of the tree representation, the root node corresponds to the entire image. Each child node represents a quadrant. The leaf node of the tree represents an area of uniform color in the image [7], [14].To keep the advantages of block-based image processing, we apply the quad-tree decomposition to blocks of size 16x16, rather than the entire image. We have tried different block sizes and choose the size of 16x16 due to the best tradeoff of implementation convenience and coding performance.

An example of the quad-tree representation is illustrated in Fig. 2, where the illustration is a block of size 8x8. Let 0 and 1 represent color green and blue, respectively. Then, if we encode the quad-tree from the root to leaves in a depth-first order, the final binary code of the quad-tree reads as

“1101101000000101010100001100010000010010101000100100010101”

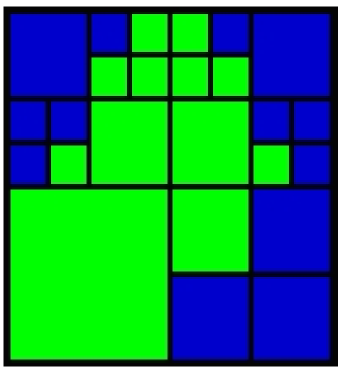

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Fig.2. block decomposition

After the color palette is generated, the input image is uniformly divided into blocks of size N by N, where N is a power of 2. The choice of block size depends on the size of the input image. Currently, we set N=32 for images with size 256x256 or larger. When input images are small, smaller N can be used. The smallest N used is 8. Blocks are processed in a raster scan order. For each block, the number of colors within this block will be examined. Each color is coded using one byte. The value of that byte is the index of the color in the palette. At any stage of subdivision, if a block or a sub-block contains exactly two colors, the binary bit pattern showing the position of each color needs to be coded as well. Fig.3. shows the quad tree decomposition of an image.

Fig.3.Quadtree Decomposition

4.2. Region splitting and merging

In region-based methods, a lot of literature has investigated the use of primitive regions as a preprocessing step for image segmentation [10]–[12]. The advantages are twofold. First, regions Carry on more information in describing the nature of objects. Second, the number of primitive regions is much fewer than that of the pixels in an image and thus largely speeds up the region-merging process. Starting from a set of primitive regions, the segmentation is conducted by progressively merging the similar neighboring regions according to a certain predicate, such that a certain homogeneity criterion is satisfied. In previous works, there are region-merging algorithms based on statistical properties [13], [3], [4], [15], graph properties. Fig.3. shows the example of region partition. Automatic image segmentation can be phrased as an inference problem [7]. For example, we might observe the colors in an image, which are caused by some unknown principles. In the context of image segmentation, the observation of an image is given, but the partition is unknown. In this respect, it is possible to formulate the inference problem as finding some representation of the pixels of an image, such as the label that each pixel is assigned. With these labels, an image is partitioned into a meaningful collection of regions and objects.

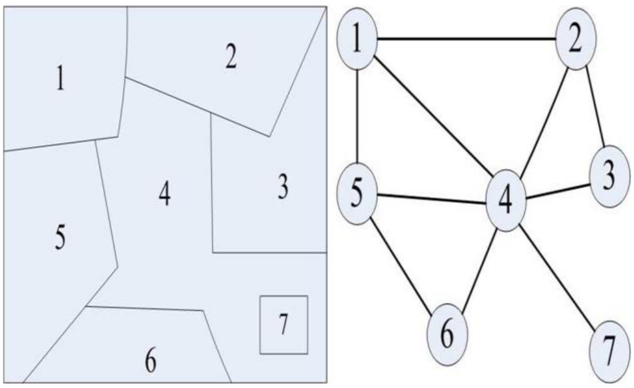

Fig.3. Example of region partition

For example, they imply some well-defined perceptual formulations for image segmentation, such as homogeneous, continuity, and similarity. In the family of region-merging techniques, some methods have used statistical similarity tests [13], to decide the merging of regions, where a predicate is defined for making local decisions. These are good examples of considering the homogeneity characteristics within a region, from which we can see that an essential attribute for region merging is the consistency of data elements in the same region. In other words, if neighboring regions share a common consistency property, they should belong to the same group. Fig.4. shows the splitting and merging process. The input image undergoes the process of image analysis the the splitting and merging process i.e., the partition of image and we have calculated the similar histogram bins.

Fig.4. Splitting and merging process

However, most of the existing region-merging algorithms cannot guarantee a globally optimal solution of the merging result. As a consequence, the region-merging output is over merged, under merged, or a hybrid case. Here, we propose a novel predicate that leads to certain global properties for the Segmentation result.

4.3. Histogram Clustering

Neighbor bins of the histogram are clustered from a previously partitioned image. After assuming that the split-and-merge algorithm provides us with the structure of the image, our clustering algorithm tries to preserve the correlation between the clustered bins and the structure of the image. Fig.5. represents the histogram clustering process. After assuming that the split-and-merge algorithm provides us with the structure of the image, our clustering algorithm tries to preserve the correlation between the clustered bins and the structure of the image

Fig.5. Histogram clustering for 3 segments

The basic idea underlying our histogram clustering algorithm is to capture the maximum information of the image with the minimum number of histogram bins. Analogous to the merging algorithm of the previous section, the loss of Mutual Information due to the clustering of two neighbor bins. Fig.6. represents the separation of histogram bins. Neighbor bins of the histogram are clustered from a previously partitioned image.

4.4. Registration Based Segmentation

Two different algorithms are presented. The first one segments just one image at a time, while the second one segments both simultaneously. The clustering process works by extracting from each image the structures that are more relevant to the other one. In these algorithms, each image is used to control the quality of the segmentation of the other. Two different algorithms are presented. The first one segments just one image at a time, while the second one segments both simultaneously. The clustering process works by extracting from each image the structures that are more relevant to the other one. In these algorithms, each image is used to control the quality of the segmentation of the other.

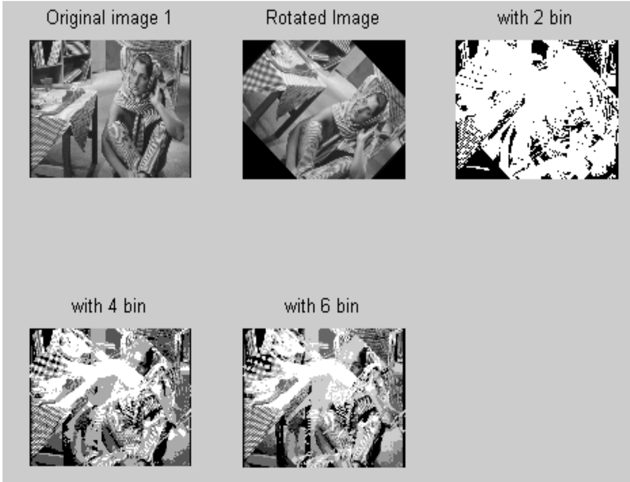

Fig.6. Co- clustering

Image registration methodology

Image registration, as it was mentioned above, is widely used in remote sensing, medical imaging, computer vision etc. In general, its applications can be divided into four main groups according to the manner of the image acquisition.
Different viewpoints (multiview analysis). Images of the same scene are acquired from different viewpoints. The aim is to gain larger a 2D view or a 3D representation of the scanned scene. Different times (multi temporal analysis). Images of the same scene are acquired at different times, often on regular basis, and possibly under different conditions Fig.7.Represents the clustering for segmentation of registration based systems.

Fig.7. Registration based clustering for 3 segments

5. CONCLUSION

General framework for image segmentation based on a hard version of the information bottleneck method. Some of the different segmentation algorithms have been introduced. The main advantages of these methods are that do not assume any *a priori* information about the images (e.g., intensity probability distribution) and that take into account the spatial distribution of the samples. Different experiments on both natural and medical images and comparisons with standard methods have shown the good behavior of the proposed algorithms. Then plan to explore the application of these methods to image fusion and level-of-detail applications with genetic algorithms. There are several potential extensions to this work, such as the introduction of global refinement and user interaction, etc. Those will be further investigated in our future work.

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