AN EFFICIENT AND EFFECTIVE IMAGE SEGMENTATION INTERACTIVE TOOL

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Abstract: This paper describes a utilization of a very efficient polynomial time algorithm, discovered by Hochbaum (2001), for segmentation tool through Markov Random Fields. The tool allows flexible choice of input parameters, controlling the output within an interactive tool with dynamic features and easily modified parameters.

1 INTRODUCTION

Image segmentation is one of the most fundamental and challenging problems in computer vision with applications, such as pattern recognition, object detection, and medical imaging. The procedures engaged for solving many of the segmentation problems with large size data sets, apply heuristics and approximations techniques, which use approaches such as aggregation, preprocessing with clustering, sampling, spectral analysis or decomposition. These methods are limited by the quality of the heuristics and are computationally too expensive to be used in many practical images and certainly not in interactive settings.

In many image segmentation problems, a human user can easily see the segments, patterns and features. This human ability has occasionally been recruited to aid segmentation. Here we are concerned with images where a human user *cannot* differentiate important and salient features. Instead, the segmentation algorithm is used to bring forth these features and very efficiently.

This paper presents an efficient segmentation method and its interactive use in order to detect features that are not visible to a human user in the noisy input image. As such it is capable of identifying tumors and other pathologies in noisy medical images, or in images where an adversary is hiding certain objects. The tool presented is tested on brain images (Collins et al., 1998). We show that lesions that are difficult to detect in the input image can be identified with the use of the methodology proposed here.

2 THE METHODOLOGY

A noisy or corrupted image is characterized by lacking uniform color areas, which are assumed to characterize a true image. To achieve higher degree of uniform color areas, it is reasonable to assign a penalty to neighboring pixels that have different colors associated with them. On the other hand, the purpose of the segmentation is to represent the "true" image. For that purpose the given assignment of colors in the input image is considered to be the "priors" on the colors of the pixels, and as such, the best estimate available on their true labels. Therefore, any change in those priors is assigned a penalty for deviating from the priors.

The Markov Random Fields optimization problem for the image segmentation problem is to assign colors to each pixel so that the total penalty is minimized. The penalty consists of two terms. One is the *separation* penalty term and the second is the *deviation* penalty term. For this reason we refer to this penalty minimization problem also as the *separation-deviation* problem (SD). This problem has been extensively studied over the past two decades, see e.g. (Geiger and Girosi, 1991; Geman and Geman, 1984). In the formulation of the MRF problem the input image has each pixel in the pixel set P associated with a color in a given set $X = \{1,\ldots,k\}$. The neighborhood of pixel i, which contains pixels adjacent to i, is denoted by $N(i)$. We wish to assign each pixel $i \in P$ an intensity $x_i \in X$ so that the sum over all pixels of the *deviation* cost $G_i(\cdot)$ and the *separation* cost $F_{ij}(\cdot)$ is minimized:

$$\text{(SD)} \quad \min D\sum_{j\in V} G_j(r_j - x_j) + S\sum_{(i,j)\in N(i)} F_{ij}(x_i - x_j),$$
$$\text{subject to } x_i \in X \quad \text{for } i \in V \ ,$$

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where the deviation function depends on the deviation of the assigned color from the given intensity, r_i and the separation is a function of the difference in assigned intensities between adjacent pixels (x_i and x_j). D and S are constant integers multiplying the deviation and separation terms respectively. If $S = 0$ then the output is the same as the input, if the colors of the input are in X, otherwise each pixel is assigned a "nearest" color label in X. If $D = 0$ then the output is a single color label assigned to all nodes. The values of S and D, if positive, are not important. Only the *ratio* of $\frac{S}{D}$ is important in determining the degree of color uniformity in the image. The larger this ratio, the greater the color uniformity.

The complexity of the separation-deviation problem depends on the form of the penalty functions. A full classification of the problem's complexity is given in (Hochbaum, 2001) showing that for convex penalty functions the problem is polynomially solvable, and for non-convex the problem is NP-hard. The cases when the deviation penalty functions are convex and the separation penalty functions are linear, for positive and negative deviations (e.g. $F_{ij}(x_i - x_j) = |x_i - x_j|$), was shown by Hochbaum (Hochbaum, 2001) to be solvable using an algorithm which is the fastest possible. For the type of problems we are interested in the choice of linear separation functions gives better results than convex quadratic ones.

3 THE INTERACTIVE TOOL AND SOME RESULTS

The empirical implementation of the separation-deviation algorithm is using a parametric minimum s,t-cut algorithm code. Our code is based on the pseudoflow algorithm of (Hochbaum, 2008) for maximum flow and minimum cut. The code is accessible for download at (Chandran and Hochbaum, 2007). Figure 1 shows the synthetic noisy image, which was used as the input in this illustration and its corresponding true brain image, (Collins et al., 1998).

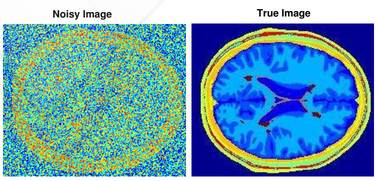

Figure 1: Brain image, Noisy and True.

The current algorithm's interface tool supports the following interactive functions:

Segment Image with a Fixed Number of Automatically Selected Colors. For a selected number of colors the tool uses a k-means algorithm to select the colors. The number of colors is not necessarily equal to the number of segments as each color set is not restricted to be a connected component.

Segment for a Specific Selected Color Set X. The user can add or remove colors from an existing color set by clicking on any pixel in the image, or manually insert the color code. As derived from the theory (outlined in an expanded version of this paper), the output image can be generated by reading the existing output and without additional computation.

Uniform Increase/Decrease in Deviation and Separation Costs. The tools allows to modify the ratio $\frac{S}{D}$. The effect of modifying this ratio is illustrated in Figure 2 for the brain images, shown in Figure 1. In that image here are four small lesions. We then apply the separation-deviation algorithm with $D = 2$ and for increasing values of S. The lesions show very clearly in the high separation images.

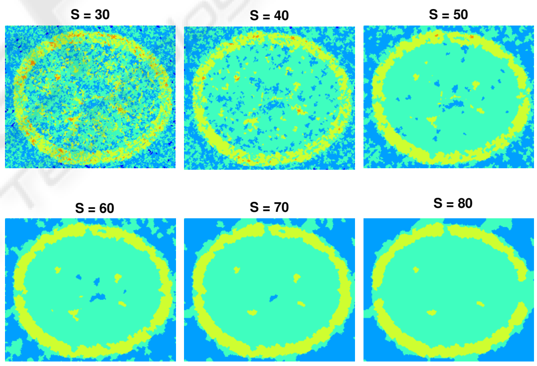

Figure 2: The output for increasing values of S when applied to noisy brain image.

Color Restricted Change in Deviation. When the user suspects that a certain color area may indicate an object of interest, it is possible to increase the deviation functions associated with this color only. So for selected color g the deviation function $G_i(x_i, g)$ is increased by the selected factor for all pixels with input color g. This guarantees that any pixel with input color equal to g is more likely to show in the segmented output, even though it is small and has unusual boundaries that otherwise would have been "cleaned" by the separation penalty dominance. When selecting, for example, in the brain image in Figure 1, the color orange, it appears as the color of 3 out of the 4 lesions, as can be seen in Figure 3. When the deviation for that color is increased the lesions become better segmented and more prominent. Of course, the color orange also appears in other areas of the brain shell where it is of no clinical significance. This issue will be addressed in the next prototype of the interactive tool, where the deviation increase will apply only in a user-defined window.

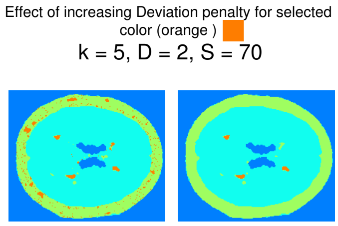

Figure 3: Increased deviation penalty for a selected color in brain image.

Choose Neighborhood Adjacency. Neighborhood is commonly referred to 8-or a 4-neighbor adjacency. The algorithm is independent of planarity or any other graph properties. The neighborhood thus is not restricted to the 4-neighbor setup that is the most common in other image segmentation algorithms. Any other type of neighborhood can be used, but an interface creating the corresponding graph is required.

4 CONCLUSIONS

We demonstrate here that the interactive tool segments successfully the salient features in true images, and can identify hidden important features and handle efficiently noisy images. As such the separation deviation interactive tool and algorithm is a useful addition to a segmentation tool box which considerably enhances current capabilities.

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