Combining Brightness, Colour and Texture Cues for Boundary Detection in Medical Image

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ABSTRACT

Background: Detection of boundaries in medical images is the challenging task and it plays a basic element in image analysis. For image segmentation and image object description, boundaries provide most important information. In this paper, a novel method to detect the boundary which combines brightness, color and texture cues to obtain the dominant boundaries of the images are proposed. The gradient is measured by the difference in mean values of the features that lie in rectangular regions around the pixel along four orientations. These gradients are combined to get a final boundary map from which the dominant boundaries are extracted. The results of this proposed method yields the better results compared to the other methods.

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INTRODUCTION

Boundary detection is often performed in medical image processing to identify the various regions of interest. It is a useful preprocessing step for performing segmentation and later recognition or diagnosis. Traditionally, there are a number of techniques available for edge detection ranging from the Sobel and Canny filters to advanced vector field convolution snake model. Unfortunately most of these methods are struggled to extract the correct boundaries of medical images.

In earlier methods, boundaries of images are detected only through local measurements. The Roberts (L. G. Roberts, 1965), Sobel (O. Duda et. al 1973), and Prewitt (S. Prewitt, 1970) operators detect edges by convolving a grayscale image with local derivative filters. Marr and Hildreth (D. Marr and E. Hildreth, 1980) used zero crossings segments from different channels of Laplacian of Gaussian operator. The Canny edge detector (J. Canny, 1986) also models edges as sharp discontinuities in the brightness channel, adding non-maximum suppression and hysteresis thresholding steps. By considering the response of the image to a family of filters of different scales and orientations, a richer description can be obtained. Perona, P et.al ( Perona, P. Malik, J. 1990) developed a two-dimensional approach which represents multiple edges at the same location through which the orientation has been determined. M.C Morrone et. al (M. C. Morrone and R. Owens, 1987) and W. T. Freeman et. al (William T. Freeman Edward H. Adelson, 1991) discussed the energy oriented approaches which uses quadrature pairs of even and odd symmetric filters. Lindeberg (T. Lindeberg, 1988) proposes a filter-based method with an automatic scale space edge selection mechanism.

In recent years, several methods are proposed to solve the problem of boundary detection. These methods taken into account color, brightness, texture channels and cue combining techniques as the prime focus. Martin et al. (D. Martin et. al ,2004), proposed a method to detect the boundaries of an image using the combined changes in brightness, color and texture of natural boundaries. Julien et. al (Mairal and Leordeanu, 2008) presented a multi-scale discriminative framework applied to detect the boundaries and which proves the improved results. A supervised learning algorithm called Boosted Edge Learning for edge and boundary detection was proposed by Martin et. al , where large number of features with many scales were selected and modeled by the new version of Probabilistic Boosting Tree classification algorithm. This approach makes it possible to handle cues parallel in the initial classification stage. Mairal et al. (J. Mairal et. al, 2008) created both generic and class-specific edge detectors by learning discriminative sparse representations of local image patches. For each class, discriminative dictionary was learned the
reconstruction errors were obtained for each dictionary as feature input to the final classifier.

Ren (X. Ren, 2008) finds benefit in combining information from multiple scales of the local operators. Additional localization and relative contrast cues, defined in terms of the multi-scale detector output, are fed to the boundary classifier. For each scale, the localization cue captures the distance from a pixel to the nearest peak response. The active contour model (ACM), is otherwise called as snake model are providing the good framework when the disparity of image segmentation becomes more. Based on this Chan-Vese (T. F. Chan, 2001), proposed a model based on the feature of mean gray value of different regions. By the same way Qinggang and Jubai (Qinggang Wu and Jubai An, 2014), discussed the method to overcome the texture inhomogeneity and proposed a new active contour method. Ling Zhang et. al (Ling Zhang, 2014), proposed a global and local scheme based on graph cut approach to segment cervical cells in images with a mix of healthy and abnormal cells. In this method, multi-way graph cut is performed globally to split cytoplasm from the rest of the cell. Martin et. al (J. Mairal et. al, 2008) combine cues from brightness, color and texture and get accurate contours to be used in natural image segmentation.

Even though many algorithms were developed recently, it is very difficult to detect the boundaries of the noisy medial images with complex background. To extract the perfect primitives, medical images do not supports and complex in nature. To sort out this problem, we propose a novel method for boundary detection in medical images. The proposed method is based on the combination of cues from brightness, colour and texture to get accurate contours to be used in natural image segmentation. This method is well adapted for medical images and the analysis and performance comparison of the said method with the commonly used alternatives.

This paper is organized as follows. Section 2 describes the boundary description algorithm in detail followed by the experimental results in section 3. Section 4 concludes this paper.

2.0 Boundary Detection:

For a given set of $n^2$ luminance samples of an image subarea, it is necessary to find out it contains a boundary element between two regions of different uniform edge (Werner Frei and Chung-Ching Chen, 1977). The boundary detection procedures can be executed by the following steps. In the first step, the different channels are extracted from the image namely brightness, color and texture. Brightness is simply the intensity value in the grayscale version of the image; it is the observation obtained by the luminance of a visual objective. Through the intensity function $C(x, y, \lambda)$, colour can be represented and its channel is empty for grayscale images and for color images it is the chrominance components of the image in Lab color space. Texture provides us the information on spatial array of color in an image and there are several methods to represent it. In this paper Gabor filter responses of the image are selected because they can represent the texture features in various orientations and scales. It has been successfully used in the areas of texture classification and retrieval of images. Four orientations at three different scales are used giving rise to twelve texture channels. Some channels for two images – peppers and a retinal fundus image are shown in fig 2.1. The magnitude of Gabor kernels are shown in fig 2.2.

![Fig. 2.1: Channels (a) Image (b) Brightness (c, d) Chrominance (e) One Texture channel.](image-url)
During the second step is to get the contour strength at every pixel. The contour strength is measured at three different scales namely \( w, 2w \) and \( w/2 \). For a given channel and scale \( w \) the contour strength at pixel location \( (x,y) \) is measured as the absolute difference in the mean values of the channel intensities in two windows of size \( w \times w \) each placed on either side of the pixel according to the orientation being measured. There are four orientations: Vertical in which the windows are in the immediate top and bottom, Horizontal in which the windows are placed to the left and right, Diagonal and anti-diagonal in which the windows are oriented at 45° and 135° to the horizontal respectively. The mean can be efficiently calculated using integral images of the particular channel. If \( I \) is the integral image then the sum of values in a rectangular window formed by the points \( (A, B, C, D) \) is given by,

\[
S_{ABCD} = I_A + I_D - I_B - I_C
\]

Using the above equation, a sum over a window can be computed in four array references. This computation is performed by rotating the image in 45° in diagonal and anti-diagonal directions which is illustrated in fig 2.3. The results obtained are the normalized contour strengths and each channel produces twelve contour strength maps, one for each of the four orientations and three for window sizes. Using these different window sizes, it is easy to capture contours occurring at different scales. For each orientation, the contour strength or cues are combined to get a contour strength map. Freedom in this experiment is choosing the weights for different channels and scales. In this paper, equal ranks are assigned to each of the texture channel maps and they are combined to get a single texture channel map for all orientation. Each one are assigned with the combined contour maps of color, brightness and texture of equal weights.

The contour maps for the four orientations are finally combined to get the contour strength map of the image. The combination is done by taking the maximum of the contour strengths are along four orientations. To avoid thick contours, non-local maxima are suppressed in the contour strength maps.
before the final combination. The suppression is carried out along a line in the respective direction.

The final step is the dominant contour extraction. Here the contour strength map is processed by assigning those pixels to zero which are smaller than 80% of the maximum value in a small neighborhood of the pixel. Then the contour is traced by starting at the maximum pixel and following the other maximum pixel in its 8-connected neighborhood. The entire contour is traced till the values drop below a threshold. Then the entire procedure is started with the largest pixel remaining. This process is limited to get a pre-specified number of contour pixels. The optimum values for these parameters usually come from the application i.e., the particular modality of the medical image and the task at hand. Stray contour pixels are cleaned to get the final contours. The complete workflow is illustrated in fig 2.4.

The Gabor kernels effectively capture the texture information which dominates in the medical images. Segmentation based on texture allows us to effectively separate the medical image into its constituent objects. The use of integral images to calculate the features makes the method computationally efficient and scalable.

Fig. 2.4: Workflow of Boundary Detection.

3.0 Results and analysis:

The given boundary detection algorithm was implemented in MATLAB and experiments were conducted on several medical images belonging to a variety of modalities. The weighting factors were chosen to according to the particular modality. In general the brightness and color channel contours are given a large weightage. The contours extracted from using a large window size i.e. at a larger scale are given less weightage. Then the method was tested on two synthetic images shown in fig 3.1 and their results are shown in fig 3.2. The images are characterized by the presence of contours of different contrast and orientations. The experiment is conducted on noisy versions of the images so that the performance in the presence of noise can be seen. Gaussian noise of medium intensity is added to the images. The output from Canny detector includes several spurious contours, while Sobel, Prewitt and Roberts’s detectors miss several contour pixels and contain spurious contours. In addition to indicating the contour pixels the result of the proposed method also gives a measure of the strength of the contours. This enables us to get the most important boundaries present in the image. To get a quantitative measure of the performance of the method Pratt’s Figure of Merit is used. The noiseless versions of the synthetic image can be used to get the ground truth boundaries. It is defined as:

$$FM = \frac{1}{\max(I_A, I_I)} \sum_{i=1}^{l_i} \frac{1}{1 + d_i a^2}$$

where $I_A, I_I, d$, and $a$ the detected edges, the ideal edges, the distance between the actual and the ideal edges, and a design constant are respectively which is used to penalize displaced edges. The measures for the two synthetic images under Gaussian noise are given in Figure 8. The superior performance of the proposed method can be easily observed.
Fig 3.1: Synthetic Images used in experiments.

<table>
<thead>
<tr>
<th>Method</th>
<th>Figure of Merit Synthetic Noisy Image 1</th>
<th>Figure of Merit Synthetic Noisy Image 2</th>
</tr>
</thead>
<tbody>
<tr>
<td>Prewitt</td>
<td>0.3507</td>
<td>0.4132</td>
</tr>
<tr>
<td>Roberts</td>
<td>0.3485</td>
<td>0.3576</td>
</tr>
<tr>
<td>Sobel</td>
<td>0.5225</td>
<td>0.4158</td>
</tr>
<tr>
<td>Canny</td>
<td>0.0672</td>
<td>0.0881</td>
</tr>
<tr>
<td>Proposed</td>
<td>0.6904</td>
<td>0.7554</td>
</tr>
</tbody>
</table>
4.0 Conclusion:
A simple but effective method to detect boundaries in medical images is presented. The method makes use of brightness, color and texture channels to detect contours in four different orientations. The contour cues are then combined and a final contour strength map is derived and the boundary is calculated from it. The proposed boundary detection technique detect the boundaries in complex medical images with high accuracy comparing with the existing contour models and the results are robust to noise.

REFERENCES


