

Medical Images Boundary Detection Using A New Novel Algorithm And Gradient Features

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Abstract

Snakes, or active contours, have been widely used in image processing applications. Typical roadblocks to consistent performance include limited capture range, noise sensitivity, and poor convergence to concavities. This paper proposes a new external force for active contours, called vector field convolution (VFC), to address these problems. VFC is calculated by convolving the edge map generated from the image with the user defined vector field kernel. We propose two structures for the magnitude function of the vector field kernel, and we provide an analytical method to estimate the parameter of the magnitude function. Mixed VFC is introduced to alleviate the possible leakage problem caused by choosing inappropriate parameters. We also demonstrate that the standard external force and the gradient vector flow (GVF) external force are special cases of VFC in certain scenarios. Examples and comparisons with GVF are presented in this paper to show the advantages of this innovation, including superior noise robustness, reduced computational cost, and the flexibility of tailoring the force field.

Index Terms—Active contours, deformable models, external force, gradient vector flow (GVF), snakes, vector field convolution (VFC).

1. Introduction

A problem of fundamental importance in image analysis is edge detection. Edges characterize object boundaries and are therefore useful for segmentation, registration, identification of objects in scenes. Image segmentation is an initial step before performing high-level tasks such as object recognition and understanding. Image

segmentation is typically used to locate objects and boundaries in images. In medical imaging, segmentation is important for feature extraction, image measurements, and image display. In some applications it may be useful to extract boundaries of objects of interest from ultrasound images, microscopic images, magnetic resonance (MR) images, or computerized tomography (CT) images. Segmentation techniques can be divided into classes in many ways, depending on the classification scheme. The most commonly used segmentation techniques can be categorized into two classes, i.e., edge-based approaches and region-based approaches. The strategy of edge-based approaches is to detect the object boundaries by using an edge detection operator and then extract boundaries by using the edge information.

The problem of edge detection is the presence of noise that results in random variation in level from pixel to pixel. Therefore, the ideal edges are never encountered in real images. A great diversity of edge detection algorithms have been devised with differences in their mathematical and algorithmic properties such as Roberts, Sobel, Prewitt, Laplacian, and Canny, all of which are based on the difference of gray levels. The difference of gray levels can be used to detect the discontinuity of gray levels. On the other hand, region-based approaches are based on similarity of regional image data. Some of the more widely used approaches are thresholding, clustering, region growing, and splitting and merging. However, the performance evaluation of image segmentation results is still a challenging problem as they fail to extract the correct boundaries of objects in noisy images.

In recent years, there have been several new methods to solve the problem of boundary detection, e.g., active contour model (ACM),

geodesic active contour (GAC) model, active contours without edges (ACWE), gradient vector flow (GVF) snake model, vector field convolution (VFC) snake model, etc. The snake models have become popular especially in boundary detection where the problem is more challenging due to the poor quality of the images.

Most algorithms for detecting the correct boundaries of objects have difficulties in medical images in which ill-defined edges are encountered. To overcome this problem, we propose a novel edge technique for boundary detection for ill-defined edges in noisy and medical images using a edge following. The proposed edge following technique is based on the vector image model and the edge map.

This paper is organized as follows. Section 2 describes the proposed technique. In section 3, we show the experimental results on the synthetic noisy images, prostate ultrasound images, and knee joints in CT images. Section 4 concludes this paper.

2. Boundary Extraction Algorithm

2.1 Average Edge Vector Field Model

An example of the edge vector field and average edge vector field is displayed in Fig. 1. Fig. 1(b) and (c) shows the results of the edge vector field and average edge vector field of the original image in Fig. 1(a). From the result, we can see that our proposed edge vector field yields more descriptive vectors along the object edge than that of the original edge vector field.

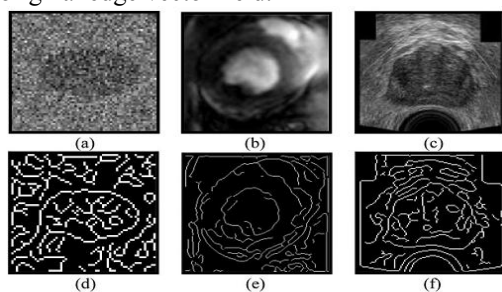


Figure 1. (a) Synthetic noisy image. (b) Left ventricle in the MR image. (c) Prostate ultrasound image. (d)–(f) Corresponding edge maps derived from Law's texture and Canny edge detection.

This idea is exploited for the boundary extraction algorithm objects in unclear images.

However, in an unclear image, the vectors derived from the edge vector field may distribute

randomly in magnitude and direction. Therefore, we extend the capability of the previous edge vector field by applying a local averaging operation where the value of each vector is replaced by the average of all the values in the local neighbourhood.

2.2 Edge Map

Edge map is edges of objects in an image derived from Law's texture and Canny edge detection. It gives important information of the boundary of objects in the image that is exploited in a decision for edge following.

2.2.1 Law's Texture:

The texture feature images of Law's texture are computed by convolving an input image with each of the masks. Given a column vector $L = (1, 4, 6, 4, 1)^T$, the 2-D mask $l(i, j)$ used for texture discrimination in this research is generated by $L \times L$. The output image is obtained by convolving the input image with the texture mask T .

2.2.2 Canny Edge Detection:

The Canny approach to edge detection is optimal for step edges corrupted by white Gaussian noise. This edge detector is assumed to be the output of a filter that reduces the noise and locates the edges. The first step of Canny edge detection is to convolve the output image obtained from the aforementioned Law's texture $t(i, j)$ with a Gaussian.

Edge map shows some important information of edge. This idea is exploited for extracting objects' boundaries in unclear images.

2.2.3 Edge Following Technique

The edge following technique is performed to find the boundary of an object. Most edge following algorithms take into account the edge magnitude as primary information for edge follows. However, the edge magnitude information is not efficient enough for searching the correct boundary of objects in noisy images because it can be very weak in some contour areas.

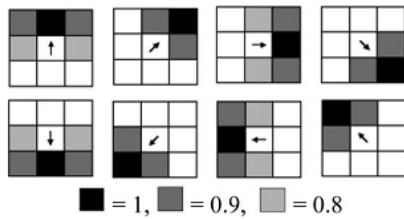


Figure 2. Edge masks used for detecting image edges

This is exactly the reason why many edge following techniques fail to extract the correct boundary of objects in noisy images. To remedy the problem, we propose an edge following technique by using information from the average edge vector field and edge map. It gives more information for searching the boundary of objects and increases the probability of searching the correct boundary. The magnitude and direction of the average edge vector field give information of the boundary which flows around an object. In addition, the edge map gives information of edge which may be a part of object boundary. Hence, both average edge vector field and edge map are exploited in the decision of the edge following technique. At the position (i,j) of an image, the successive positions of the edges are then calculated by a 3×3 matrix.

3. Experimental Results

We tested the performance of the proposed method by comparing its results with the results from five classical contour models. We also computed the probability of error in boundary detection and the Hausdorff distance of the six methods by comparing their results with the opinion from expert medical doctors. Finally, we tested the efficiency of time consumption by comparing running times of the six methods. Each input image was pre-processed by a 3×3 median filter prior to the application of each method.

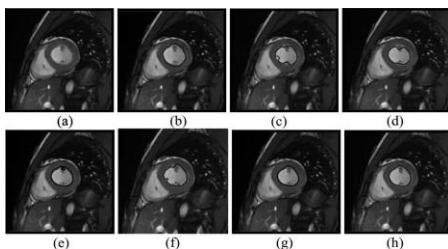


Figure 3. Left ventricle in cardiac MR images. (a) Original image. (b) Doctor's delineation. Results of (c) ACM, (d) GAC, (e) ACWE, (f) GVF, (g) VFC, and (h) the proposed technique.

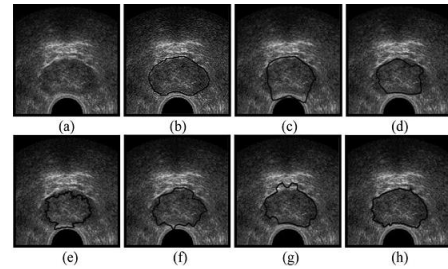


Figure 4. Prostate ultrasound images. (a) Original image. (b) Doctor's delineation. Results of (c) ACM, (d) GAC, (e) ACWE, (f) GVF, (g) VFC and (h) the proposed technique.

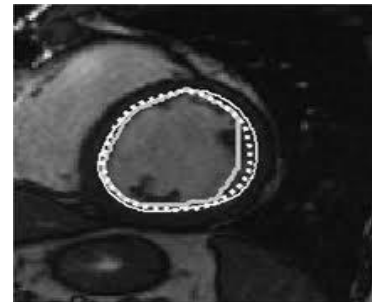


Figure 5. Segmentation in Cardiac MRI Image

The proposed method was first implemented on synthetic images. The synthetic images were generated from the original binary image by corrupting them with additive white Gaussian noise. We did this to make sure that the ground truths of the boundaries were known. Several synthetic images were tested and the intuitive results were achieved, i.e., the boundary detection results from the images with higher signal-to-noise ratio were better than that with lower ratio. We further tested our method to detect object boundaries in some types of medical images including prostates in ultrasound images, left ventricles in cardiac MR images, aortas in cardiovascular MR images, and knee joints in CT images. The prostate ultrasound images were obtained from the CIMI Lab's website of the Nanyang Technological University and UW image computing systems lab. The cardiac MR images of left ventricles were obtained from York University and Medical School, Chiang Mai University (CMU.) The cardiovascular MR images of aortas were obtained from Imaging Consult website and Medical.

4. Conclusion

In this paper, a novel static external force for active contours, called the vector field convolution (VFC), has been introduced. The VFC field is calculated by convolving a vector field kernel with the edge map generated from the image. We proposed two classes of magnitude functions for the vector field kernel. We showed that the GVF field in homogeneous regions of the image is a special case of a VFC field. Several promising properties of VFC have been demonstrated by extensive examples. We have shown that the VFC snakes have large capture ranges, and converge to boundary concavities, similar to the GVF snakes. Additionally, the VFC snakes are less computationally expensive, more robust to noise and initialization than GVF snakes. VFC can also be easily customized and enhanced for different applications.

Designed a new edge following technique for boundary detection and applied it to object segmentation problem in medical images. Our edge following technique incorporates a vector image model and the edge map information. The proposed technique was applied to detect the object boundaries in several types of noisy images where the defined edges were encountered. The proposed technique's performances on object segmentation and computation time were evaluated by comparing with five popular methods, i.e., the ACM, GAC, ACWE, GVF, and VFC snake models. Several synthetic noisy images were created and tested for the sake of the known ground truths. The opinions of the skilled doctors were used as the ground truths.

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References

- [1] M. Kass, A. Witkin, and D. Terzopoulos, "Snakes-active contour models," *Int. J. Comput. Vis.*, vol. 1, pp. 321–331, 1987.
- [2] D. Terzopoulos, A. Witkin, and M. Kass, "Constraints on deformable models-recovering 3D shape and nonrigid motion," *Artif. Intell.*, vol. 36, pp. 91–123, 1988.
- [3] M. Gastaud, M. Barlaud, and G. Aubert, "Combining shape prior and statistical features for active contour segmentation," *IEEE Trans. Circuits Syst. Video Technol.*, vol. 14, no. 5, pp. 726–734, May 2004.

[4] J.-O. Lachaud and A. Montanvert, "Deformable meshes with automated topology changes for coarse-to-fine three-dimensional surface extraction," *Med. Image Anal.*, vol. 3, pp. 187–207, 1999".

[5] T. McNemey and D. Terzopoulos, "Topology adaptive deformable surfaces for medical image volume segmentation," *IEEE Trans. Med. Imag.*, vol. 18, no. 10, pp. 840–850, Oct. 1999.

[6] T. McNemey and D. Terzopoulos, "A dynamic finite element surface model for segmentation and tracking in multidimensional medical images with application to cardiac 4D image analysis," *Comput. Med. Imag. Graph.*, vol. 19, pp. 69–83, 1995.

[7] N. Ray and S. T. Acton, "Motion gradient vector flow: An external force for tracking rolling leukocytes with shape and size constrained active contours," *IEEE Trans. Med. Imag.*, vol.23, no.12, pp.1466–1478, Dec. 2004.

[8] N. Ray, S. T. Acton, and K. Ley, "Tracking leukocytes in vivo with shape and size constrained active contours," *IEEE Trans. Med. Imag.*, vol. 21, no. 10, pp. 1222–1235, Oct. 2002.