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Segmentation of Objects in Synthetic Noisy Images

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***Abstract*— Finding the correct boundary in noisy images is still a difficult task. Our proposed method introduces a new edge following technique for boundary detection in noisy images. Utilization of the proposed technique is exhibited via its application to various types of medical images. Our proposed technique can detect the boundaries of objects in noisy images using the information from the intensity gradient via the vector image model and the texture gradient via the edge map. The performance and robustness of the technique have been tested to segment objects in synthetic noisy images and medical images including left ventricles in cardiac magnetic resonance images, aortas in cardiovascular magnetic resonance images, and knee joints in computerized tomography images. The results show that our technique performs very well and yields better performance than the classical contour models. The proposed method is robust and applicable on various kinds of noisy images without prior knowledge of noise properties.**

Index Terms—Aortas, Edge map, Tomographic Images

I. INTRODUCTION

Image synthesis operations create images from other images or non-image data. Image synthesis operations generally create images that are either physically impossible or impractical to acquire. Synthetic images are often used to verify the correctness of operators by applying them to known images. Image synthesis is the process of creating new images from some form of image description. The kinds of images that are typically synthesized include:

- Test Patterns, Scenes with simple two dimensional geometric shapes.
- Image Noise, Images containing random pixel values, usually generated from specific parameterized distributions.
- Computer Graphics, Scenes or images based on geometric shape descriptions. Often the models are three-dimensional, but may also be two-dimensional.

Synthetic images are often used to verify the correctness of operators by applying them to known images. The images could be binary, gray level or color.

There are three major benefits to digital image processing. The consistent high quality of the image, the low cost of processing and the ability to manipulate all aspects of the process are all great benefits. As long as computer processing speed continues to increase while the cost of storage memory continues to drop, the field of image processing will grow. One of the major advantages in having medical images in digital form is the ability to perform a variety of processing procedures with a computer. These procedures can be selected and adjusted to change the characteristics of the images, usually for the purpose of improving quality or optimizing characteristics for maximum visibility. Processing of digital images can be used to change most image characteristics.

Three possibilities include processing methods to:

- Reduce image noise
- Increase visibility of detail
- Adjust and optimize the image contrast characteristics.

Image processing mainly used in Visualization - Observe the objects that are not visible, Image sharpening and restoration - To create a better image, Image retrieval - Seek for the image of interest, Measurement of pattern – Measures various objects in an image, Image Recognition Distinguish the objects in an image.

One of the biggest advantages of digital imaging is the ability of the operator to post-process the image. Post-processing of the image allows the operator to manipulate the pixel shades to correct image density and contrast, as well as perform other processing functions that could result in improved diagnosis and fewer repeated examinations.

[1] presented a Conventional method to improve segmentation smoothness and immunity to noise is to model neighboringvoxels interactions using a Markov random field (MRF) statistical spatial model. MRF-based algorithms are computationally intractable unless some approximation is used which still requires computationally intensive

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algorithms. The expectation-maximization (EM) algorithm is utilized to learn the parameter-tied, constrained Gaussian mixture model. The disadvantage of this model is the classification rate is not accurate.

[2] proposed an atlas-based segmentation method employing label propagation and spatially varying decision fusion has been presented. The method evaluates the success of the registration between the atlas and the target image locally, and on that basis a weighted decision fusion is performed. The vertical range for the segmentation of the aorta was determined by the top of the aortic arch at the top of the scan, and the apex of the heart at the bottom. For the heart segmentation the vertical range was defined by the bifurcation of the pulmonary artery at the top, and the apex of the heart at the bottom. The method takes more evaluation time for execution.

[3] proposed a robust detection method used to detect and diagnose pulmonary disease. Pulmonary fissure integrity and the characteristics of tissue adjacent to the fissure may play an important role in identifying and characterizing chronic obstructive pulmonary disease and interstitial lung disease as well as the presence of early disease in general. The method provides a basis for accurate lobe segmentation that may help facilitate preoperative planning and postoperative assessment in the clinical practice. The scheme performance was evaluated by two experienced thoracic radiologists using a set of 100 images randomly selected from 10 screening CT examinations. The method performs well but its need prior knowledge about the image shapes.

[4] proposed an approach which depends on the definition of a comprehensive set of goals for the computation of edge points. These goals must be precise enough to delimit the desired behavior of the detector while making minimal assumptions about the form of the solution. The design was based on the specification of detection and localization criteria in a mathematical form. It was necessary to augment the original two criteria with a multiple response measure in order to fully capture the intuition of good detection. A detector was proposed which used adaptive thresholding with hysteresis to eliminate streaking of edge contours. A method was proposed for the efficient generation of highly directional masks at several orientations, and their integration into a single description. The disadvantage of the techniques is time consuming and tedious.

[5] proposed a statistical power transformation approach to solve the problem of non-Gaussianity, without the cost of algorithmic complexity. The proposed approach extends Gaussian mixtures to power-transformed mixtures by incorporating a shape parameter, which is intrinsically useful for modeling non-Gaussian image data. The method extends traditional Gaussian mixtures expectation-maximization segmentation to a power transformed version of mixed intensity distributions, which includes Gaussian mixtures as a special case. As MR intensities tend to exhibit non-Gaussianity due to partial volume effects, the proposed method is designed to fit non-Gaussian tissue intensity distributions. Even though method shows good performance, it needs additional computation time.

Active contour models (ACM) - Active contour model, also called snakes, are a framework for delineating an object outline from a possibly noisy 2D image. This framework attempts to minimize an energy associated to the current contour as a sum of an internal and external energy. The external energy is supposed to be minimal when the snake is at the object boundary position. The internal energy is supposed to be minimal when the snake has a shape which is supposed to be relevant considering the shape of the sought object.

Geodesic active contour models - The technique is based on active contours evolving in time according to intrinsic geometric measures of the image. The evolving contours naturally split and merge, allowing the simultaneous detection of several objects and both interior and exterior boundaries. The proposed approach is based on the relation between active contours and the computation of geodesics or minimal distance curves. The scheme was implemented using an efficient algorithm for curve evolution.

Active contours without edges - The main goal of this report, in terms of application, are to solve the image segmentation problem. This method utilizes the level set technique of curve treatment and more importantly, overcomes several difficulties arising in previous methods of image segmentation. The main difficulty in the implementation is the first term of the PDE, the modified motion by mean curvature term. Gradient vector flow snake models - The Gradient Vector Flow (GVF) is a vector diffusion approach based on Partial Differential Equations (PDEs). This method has been applied together with snake models for boundary extraction medical images segmentation. The key idea is to use a diffusion-reaction PDE to generate a new external force field that makes snake models less sensitivity to initialization as well as improves the snake's ability to move into boundary concavities.

II. PROPOSED SYSTEM

Edge detection is a problem of fundamental importance in image analysis. In typical images, edges characterize object boundaries and are therefore useful for segmentation, registration, and identification of objects in a scene. In this section, the construction, characteristics, and performance of a number of gradient and zero-crossing edge operators will be presented. An edge is a jump in intensity. The cross section of an edge has the shape of a ramp. An ideal edge is a discontinuity. The first derivative assumes a local maximum at an edge. For a continuous image $f(x, y)$, where x and y are the row and column coordinates respectively, we typically consider the two directional derivatives $\partial_x f(x, y)$ and $\partial_y f(x, y)$. Of particular interest in edge detection are two functions that can be expressed in terms of these directional derivatives: the gradient magnitude and the gradient orientation.

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Local maxima of the gradient magnitude identify edges in f(x,y) When the first derivative achieves a maximum, the second derivative is zero. For this reason, an alternative edge-detection strategy is to locate zeros of the second derivatives of f(x,y). The differential operator used in these so-called zero-crossing edge detectors is the laplacian. Local image smoothing can effectively eliminate impulsive noise or degradations appearing as thin stripes, but does not work if degradations are large blobs or thick stripes. Edge vectors of an image indicate the magnitudes and directions of edges which form a vector stream flowing around an object. 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 neighborhood.

Edge map is edges of objects in an image derived from Law's texture and Canny edge detection. The output image is obtained by convolving the input image with the texture mask. Texture mask is $L = (1, 4, 6, 4, 1)^T$ it obtained by $L \times L^T$. The Canny edge detector is widely considered to be the standard edge detection algorithm in the industry. The steps in the canny edge detector are as follows:

▪ Smooth the image with a two dimensional Gaussian. In most cases the computation of a two dimensional Gaussian is costly, so it is approximated by two one dimensional Gaussians, one in the x direction and the other in the y direction.

▪ It is inevitable that all images taken from a camera will contain some amount of noise. To prevent that noise is mistaken for edges, noise must be reduced. Therefore the image is first smoothed by applying a Gaussian filter.

▪ The Canny algorithm basically finds edges where the grayscale intensity of the image changes the most. These areas are found by determining gradients of the image. Gradients at each pixel in the smoothed image are determined by applying what is known as the Sobel-operator.

▪ The gradient magnitudes (also known as the edge strengths) can then be determined as an Euclidean distance measure by applying the law of Pythagoras. It is sometimes simplified by applying Manhattan distance measure to reduce the computational complexity.

▪ Nonmaximal suppression to identify edges. The broad ridges in the magnitude must be thinned so that only the magnitudes at the points of the greatest local change remain.

▪ Non maxima suppression step makes all edges in M one pixel thick. This is an important step in Canny's algorithm, which distinguishes it from other algorithms. The first step is to quantize gradient direction into just four directions.

▪ The purpose of this step is to convert the 'blurred' edges in the image of the gradient magnitudes to 'sharp' edges. Basically this is done by preserving all local maxima in the gradient image, and deleting everything else.

▪ The thresholding algorithm to detect and link edges. The double threshold algorithm is used to detect and link edges.

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

▪ The edge-pixels remaining after the non-maximum suppression step are (still) marked with their strength pixel-by-pixel. Many of these will probably be true edges in the image, but some may be caused by noise or color variations for instance due to rough surfaces. The simplest way to discern between these would be to use a threshold, so that only edges stronger that a certain value would be preserved. The Canny edge detection algorithm uses double thresholding. Edge pixels stronger than the high threshold are marked as strong; edge pixels weaker than the low threshold are suppressed and edge pixels between the two thresholds are marked as weak.

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. 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 following. 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.

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.

In Initial Position, we present a technique for determining a good initial position of edge following that can be used for the boundary detection. The initial position problem is very important in the classical contour models. Snake models can converge to a wrong boundary if the initial position is not close enough to the desired boundary. In this proposed technique, the initial position of edge following is determined by the following steps.

❖ The first step is to calculate the average magnitude using the position with high magnitude should be a good candidate of strong edges on the image.
❖ The second step is to calculate the density of edge length for each pixel from an edge map. An edge map as a binary image is obtained by Law's texture and Canny edge detection.

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- The third step is to calculate the initial position map from summation of average magnitude and density of edge length,
- The last step is the thresholding of the initial position map.

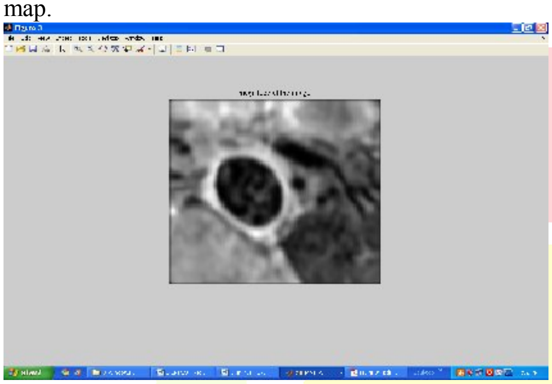

Fig.1.Magnitude of the image

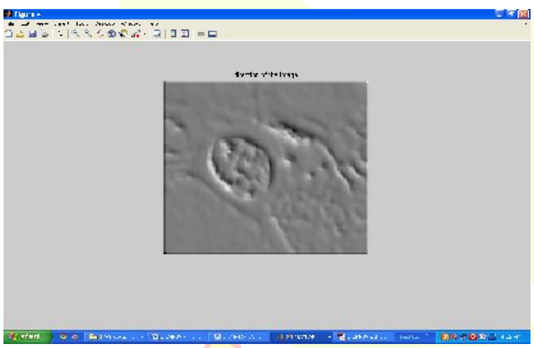

Fig.2. Direction of the image

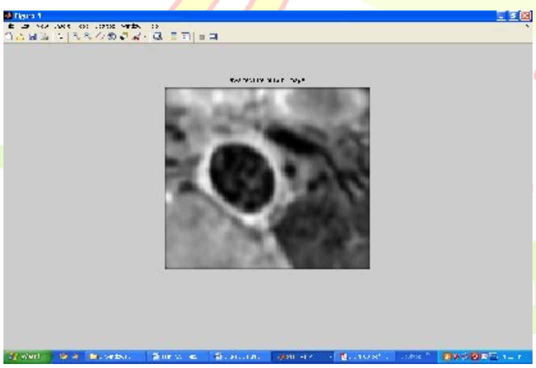

Fig.3. Law's texture output image

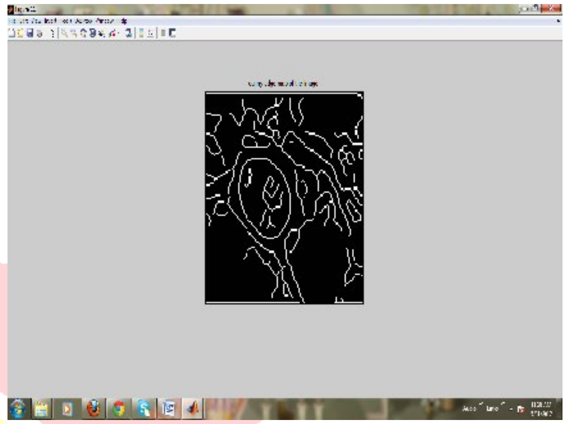

Fig.4. Canny edge map of the image

III. CONCLUSION

Finding the correct boundary in noisy images is still a difficult task. Our proposed method introduces a new edge following technique for boundary detection in noisy images. Utilization of the proposed technique is exhibited via its application to various types of medical images. Our proposed technique can detect the boundaries of objects in noisy images using the information from the intensity gradient via the vector image model and the texture gradient via the edge map. The performance and robustness of the technique have been tested to segment objects in synthetic noisy images and medical images including left ventricles in cardiac magnetic resonance images, aortas in cardiovascular magnetic resonance images, and knee joints in computerized tomography images. The results show that our technique performs very well and yields better performance than the classical contour models. The proposed method is robust and applicable on various kinds of noisy images without prior knowledge of noise properties.

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