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Diagnosis of the Abdominal Aorta Aneurysm in Magnetic Resonance Imaging Images

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***Abstract*—**This paper presents a technique for diagnosis of the abdominal aorta aneurysm in magnetic resonance imaging (MRI) images. First, our technique is designed to segment the aorta image in MRI images. This is a required step to determine the volume of aorta image which is the important step for diagnosis of the abdominal aorta aneurysm. Our proposed technique can detect the volume of aorta in MRI images using a new external energy for snakes model. The new external energy for snakes model is calculated from Law's texture. The new external energy can increase the capture range of snakes model efficiently more than the old external energy of snakes models. Second, our technique is designed to diagnose the abdominal aorta aneurysm by Bayesian classifier which is classification models based on statistical theory. The feature for data classification of abdominal aorta aneurysm was derived from the contour of aorta images which was a result from segmenting of our snakes model, i.e., area, perimeter and compactness. We also compare the proposed technique with the traditional snakes model. In our experiment results, 30 images are trained, 20 images are tested and compared with expert opinion. The experimental results show that our technique is able to provide more accurate results than 95%.

***Keywords*—**Adbominal Aorta Aneurysm, Bayesian Classifier, Snakes Model, Texture Feature.

I. INTRODUCTION

THE aorta is the largest artery in your body, and it carries oxygen-rich blood pumped out of, or away from, your heart. Your aorta runs through your chest, where it is called the thoracic aorta. When it reaches your abdomen, it is called the abdominal aorta. The abdominal aorta supplies blood to the lower part of the body. In the abdomen, just below the navel, the aorta splits into two branches, called the iliac arteries, which carry blood into each leg. When a weak area of the abdominal aorta expands or bulges, it is called an abdominal aortic aneurysm (AAA) [1]. A normal aorta is about 1 inch (or about 2 centimeters) in diameter. Aneurysms are a health risk because they can burst or rupture. A ruptured aneurysm can cause severe internal bleeding, which can lead to shock or even death. Abdominal aortic aneurysms that are not causing symptoms are most often found when a physician is performing an imaging test, such as magnetic resonance imaging and computerized tomography images.

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Magnetic resonance imaging (MRI) [2]-[4] is a non-invasive tool that can be used to measure the volume of aorta images and to diagnose the presence of abdominal aorta aneurysm. It is widely used in medical diagnosis and surgery. Aorta segmentation of MRI image is challenging due to poor image contrast and high noises. Finding the correct segmentation of aorta image is a difficulty task [5],[6]. The accurate detection of boundaries from the MR images plays a key role in many applications and essential to diagnosis and treatment procedures.

Many automated segmentation algorithms have been developed [7]-[9]. However, they fail to extract the correct boundaries in MRI images. In recent years, there have been several new methods to solve problem of boundary detection, i.e., active contour model (ACM) or snakes [10]. They have become popular especially in boundary detection and in pattern recognition where the problem is more challenging due to the poor quality of the images. Snakes represents an object boundary or some other salient image feature as a parametric curve that is allowed to deform from some arbitrary initial shape towards the desired final shape. Snakes can move a curve by using internal energy and external energy. Internal energy is defined within the curve or surfaces itself which is designed to keep the model smooth during deformation. External energy is computed from the image data which is defined to move the model toward an object boundary or other desired feature within an image. However, the weaknesses and limitations of snakes method are the capture range is very narrow and the difficulty in moving into boundary concavities [11],[12]. Snakes performs badly in cases where images contain high level of noise such as MRI imaging.

In this paper, we propose a new technique for diagnosis of the abdominal aorta aneurysm in MRI images. First, we designed a new external energy for snakes by Law's texture [13]-[14]. Law's texture is used to make a new external energy. It is devised a collection of convolution masks specifically for the purpose of computing the energy in a texture. Second, we designed a technique to diagnosis of abdominal aorta aneurysm in MRI images. The contour of new snakes model is used in finding the feature which is exploited in decision for data classification of abdominal aorta aneurysm. We used area, perimeter and compactness to decide for diagnosing the abdominal aorta aneurysm in MRI images.

The abdominal aorta aneurysm was classified by Bayesian classifier [15],[16]. Bayesian classifier is a method for classifying the presence of abdominal aorta aneurysm on closest training examples in the feature space. Finally, the results of our technique are compared with the traditional snakes model by segmenting the aorta images and diagnosing the abdominal aorta aneurysm in MRI images.

We note that part of the work reported in this paper has appeared in the conference paper [17].

II. PROPOSED TECHNIQUE

The process of all proposed technique is shown in Fig. 1. First, we segment the aorta images by our snakes model. Second, we extract the feature of contour which is derived from snakes model. Finally, we diagnose the abdominal aorta aneurysm by using Bayesian classifier.

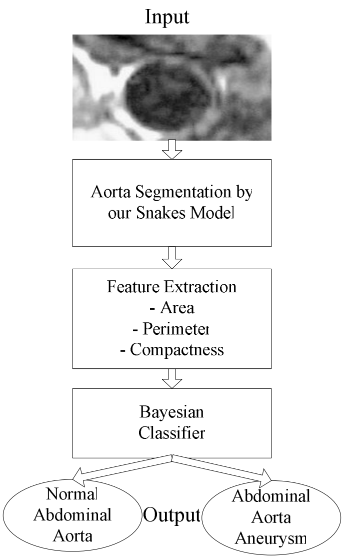

Fig. 1 The model of proposed technique

A. *Image Segmentation of Aorta Images*

The contour of snakes model is defined in the (x,y) plane of an image as a parametric curve, v(s)=(x(s),y(s)), where s is a parameter which increases as we around the contour and is related to arc length. Snakes is curves that can be moved due to the influence of internal and external energy. The mathematical model of snakes is:

$$E_{Snake} = E_{\text{int}} + E_{ext} \,, \tag{1}$$

or

$$E_{Snake} = \int_s \frac{1}{2}(\alpha(s)|v_s|^2 + \beta(s)|v_{ss}|^2) + E_{image}(v(s))ds \tag{2}$$

where

E_{int} is internal energy of the contour v(s),

E_{ext} is new external energy which is derived from Law's texture,

$\alpha(s)$ and $\beta(s)$ is weight parameter of internal energy which allows us to control the internal energy along different parts of the contour. $\alpha(s)$ controls the tension of the contour. $\beta(s)$ controls its rigidity.

E_{int} (Internal Energy)

Internal energy is a function of the contour v(s) itself and it specifies the tension and smoothness of the curve. It therefore depends on the internal properties of the snakes. The internal energy consists 2 terms, elastic energy and bending energy, i.e.,

$$E_{\text{int}} = E_{elastic} + E_{bending} \,. \tag{3}$$

The contour is treated as an elastic rubber band giving it an elastic potential energy. This energy consists of first order derivative of the contour and it discourages stretching by introducing tension in the contour, i.e.,

$$E_{elastic} = \frac{1}{2}\int_s \alpha(s)|v_s|^2 ds \tag{4}$$

where $V_s = \dfrac{dv(s)}{ds}$.

The contour of snakes should try to be a smooth curve or straight line and avoid sharp corners. Therefore the snakes is considered to possess bending energy which is given as the sum of squared curvatures of the snakes, i.e.,

$$E_{Bending} = \frac{1}{2}\int_s \beta(s)|v_{ss}|^2 ds \tag{5}$$

where $V_{ss} = \dfrac{d^2 v(s)}{ds^2}$

E_{ext} (External Energy)

External energy is an external potential energy which depends on the image. External energy is defined to move the model toward an object boundary or other desired feature within an image. External energy of the proposed method is derived from Law's texture that contains our object of interest. External image energy of the whole contour (E_{ext}) is then defined as

$$E_{ext} = \int_s E_{image}(v(s))ds \,. \tag{6}$$

The energy of Law's texture is computed by convolving an input image with each of the masks. The 2-dimensional convolution masks typically used for texture discrimination are generated from the following set of 1-dimensional convolution masks of length five:

- local averaging filter L5=(1,4,6,4,1)
- edge detector E5=(–1,–2,0,2,1)
- spot detector S5=(–1,0,2,0,–1)
- ripple detector R5=(1,–4,6,–4,1)
- wave detector W5 =(–1,2,0,–2,1)

$$\begin{bmatrix} -1 \\ -2 \\ 0 \\ 2 \\ 1 \end{bmatrix} \times \begin{bmatrix} 1 & 4 & 6 & 4 & 1 \end{bmatrix} = \begin{bmatrix} -1 & -4 & -6 & -4 & -1 \\ -2 & -8 & -12 & -8 & -2 \\ 0 & 0 & 0 & 0 & 0 \\ 2 & 8 & 12 & 8 & 2 \\ 1 & 4 & 6 & 4 & 1 \end{bmatrix}$$

E5 L5 = E5 × L5

$$\begin{bmatrix} 1 \\ 4 \\ 6 \\ 4 \\ 1 \end{bmatrix} \times \begin{bmatrix} -1 & -2 & 0 & 2 & 1 \end{bmatrix} = \begin{bmatrix} -1 & -2 & 0 & 2 & 1 \\ -4 & -8 & 0 & 8 & 4 \\ -6 & -12 & 0 & 12 & 6 \\ -4 & -8 & 0 & 8 & 4 \\ -1 & -2 & 0 & 2 & 1 \end{bmatrix}$$

L5 E5 = L5 × E5

Fig. 2 Law's mask is computed from E5 × L5 and L5 × E5 which is used in our method

If we multiply the column vectors and row vectors, we obtain 25 Law's masks. We can obtain the output image $t(i,j)$ by convolving the input image with texture masks, i.e.,

$$t(i,j) = l(i,j) * f(i,j)\,, \tag{7}$$

$$t(i,j) = \sum_{m=-2}^{m=2} \sum_{n=-2}^{n=2} l(m,n) f(i+m, j+n)\,, \tag{8}$$

where

$l(i,j)$ is 2-D masks from Law's. texture,

$f(i,j)$ is input image,

$t(i,j)$ is obtained by convolving the input image with texture masks.

After we can obtain the output images $t(i,j)_{L5E5}$ and $t(i,j)_{E5L5}$, the energy of texture is calculated by using the formula:

$$E_{Texture}(i,j) = \left|t(i,j)_{L5E5}\right| + \left|t(i,j)_{E5L5}\right| \tag{9}$$

The way to defined E_{image} which push snakes contour towards edges is

$$E_{image} = G_\sigma(i,j) * \left(\left|t(i,j)_{L5E5}\right| + \left|t(i,j)_{E5L5}\right|\right) \tag{10}$$

where

$E_{Texture}(i,j)$ is energy of image which is derived from Law's Texture,

$G_\sigma(i,j)$ is a 2-dimensional Gaussian Function with standard deviation,

$t(i,j)_{L5E5}$ is energy of image which is computed by convolving the Law's Masks of L5E5 with input image,

$t(i,j)_{E5L5}$ is energy of image which is computed by convolving the Law's Masks of E5L5 with input image.

The external energy which is computed from traditional external energy can't push the contour into boundary concavities of object. The new external energy can push the contour into boundary concavities of object. The comparisons of the result of the proposed technique with the old external energy are shown in Fig. 3.

B. Feature Extraction of Aorta Images

The basic idea in data classification is to recognize objects based on features. The feature for an object can be represented as a point in the N-dimensional feature space defined for that particular object recognition task. In diagnosis of the abdominal aorta aneurysm, we used three features which is derived form the contour of our snakes model, i.e.,

$$Area = \sum_{i=1}^{n} \sum_{j=1}^{m} B(i,j)\,, \tag{11}$$

$$Perimeter = \sum_{i=1}^{n} \sum_{j=1}^{m} P(i,j)\,, \tag{12}$$

$$Compactness = \frac{P^2}{A}\,, \tag{13}$$

where

$B(i,j)$ is image pixel of area,

$P(i,j)$ is image pixel of perimeter.

The area is the number of pixels in the contour. The perimeter is lengths of the contour. It is sum of pixel separating region from background. *P* and *A* are the figure's perimeter and area. Compactness is shape of circle. A circle is the most compact figure (i.e., has the smallest compactness value) according to this measure.

C. Diagnosis of the Abdominal Aorta Aneurysm

Bayesian classifiers are classification models based on statistical theory. Bayesian classifier is used for diagnosing of the abdominal aorta aneurysm in MRI images. We can use three features in diagnosing the abdominal aorta aneurysm.

The three features can specify the normal aorta image and abnormal aorta image (abdominal aorta aneurysm). In diagnosing of abdominal aorta aneurysm by Bayesian classifiers, the first step calculated the mean value of each feature vector by using the formula:

$$\vec{\hat{\mu}} = \frac{1}{n}\sum_{k=1}^{n} \vec{x}_k \tag{14}$$

Second step, we calculated the covariance matrix by using the formula:

$$\overset{=}{\varepsilon} = \frac{1}{n}\sum_{k=1}^{n} (\vec{x}_k - \vec{\hat{\mu}})^T (\vec{x}_k - \vec{\hat{\mu}}) \tag{15}$$

Finally step, we decided in diagnosing of the abdominal aorta aneurysm by using the formula:

$$p(\vec{x}/w_i) = \frac{1}{(2\pi)^{n/2}\left|\overset{=}{\varepsilon_i}\right|^{-1/2}} \exp(-\frac{1}{2}(\vec{x}-\mu_i)^t \overset{=}{\varepsilon}_i^{-1}(\vec{x}-\mu_i)) \tag{16}$$

$$P(w_i/\vec{x}) = \frac{p(\vec{x}/w_i)P(w_i)}{p(\vec{x})} \tag{17}$$

$$p(\vec{x}) = \sum_{i=1}^{n} p(\vec{x}/w_i)P(w_i) \tag{18}$$

where

$p(\vec{x}/w_i)$ is the likelihood function of w_i with respect to $\vec{x}$. $P(w_i)$ is priori probability. $p(\vec{x})$ is probability density function (pdf). The Bayes classification rule can now be stated as:

If $P(w_1/\vec{x}) > P(w_2/\vec{x})$, $\vec{x}$ is classified to w_1.

If $P(w_1/\vec{x}) < P(w_2/\vec{x})$, $\vec{x}$ is classified to w_2.

w_1 is a normal abdominal aorta. w_2 is a abnormal abdominal aorta (abdominal aorta aneurysm).

III. Experimental Results

This section shows the examples of results of our proposed. The first experimental results, we tested the result of segmenting the synthetic images and the aorta images in MRI images. We compared the new snakes model with the tradition snakes model by using the opinions of the skilled doctor as the ground truth. To make the comparison fair to all methods, their initial contours are selected manually. The comparisons of the result for image segmentation are shown in Fig. 3 and Fig. 4. From traditional snakes model and new snakes model, we used the same weight parameter in testing of image segmentation. In addition to the virtual inspection, we evaluate our segmentation technique numerically using the probability of error in image segmentation, i.e.,

$$PE = P(O)P(B\,|\,O) + P(B)P(O\,|\,B), \tag{17}$$

where

$P(O)$ and $P(B)$ are a priori probabilities of objects and background in images,

$P(B\,|\,O)$ is the probability of error in classifying objects as background,

$P(O\,|\,B)$ is the probability of error in classifying background as objects.

The ground truth images were given by a doctor. The results of probability of error in segmentation (PE) of the proposed technique and traditional snakes model which is compared to an expert's opinions are shown in Table I.

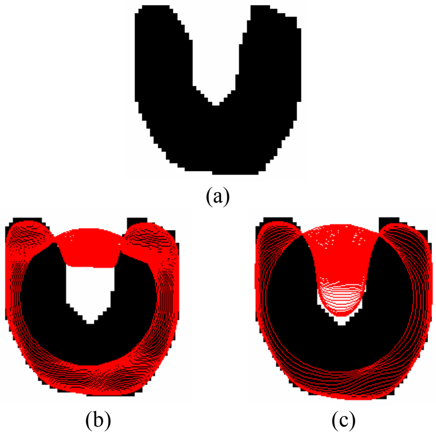

Fig. 3 (a) Synthetic image (b) Results from tradition snakes model (c) Results from new snakes model

From Fig. 3 we can see that the traditional snakes model can not move the contour into boundary concavities but the new snakes model can move the contour into boundary concavities.

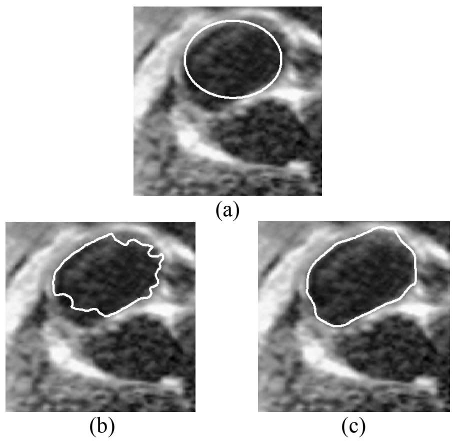

Fig. 4 (a) Original image and initial contour (b) Results from the traditional snakes model (c) Results from the new snakes model

TABLE I
RESULTS OF PROBABILITY OF ERROR IN IMAGE SEGMENTATION (PE) BY COMPARING BETWEEN TRADITIONAL SNAKES MODEL AND NEW SNAKES MODEL

Image	Traditional Snakes		Proposed technique	
	Synthetic images	Aorta Images	Synthetic Images	Aorta images
1	9.56%	12.91%	2.34%	9.21%
2	7.87%	15.54%	3.62%	11.31%
3	11.23%	15.51%	4.55%	14.21%
4	10.44%	13.44%	6.21%	12.43%
5	13.54%	16.43%	5.93%	12.04%
6	12.11%	13.96%	6.64%	8.65%
7	14.54%	12.45%	7.12%	11.76%
8	6.76%	16.21%	8.92%	10.34%
9	8.65%	8.35%	5.74%	13.79%
10	10.38%	11.43%	7.81%	11.51%
Average	10.50%	13.62%	5.88%	11.52%

The second experimental results, we tested the result of diagnosing the abdominal aorta aneurysm. We used 30 images for training the data (15 images of normal aorta and 15 images of abnormal aorta). This is the image data which is classified by doctor opinion. The feature of 30 images are computed from area, perimeter and compactness of each images. We used 20 images for testing the data (10 images of normal aorta and 10 images of abnormal aorta). The normal aorta and abnormal aorta are classified by Bayesian classifier. We tested the efficiency of proposed technique and the traditional snakes models by using the opinions of the skilled doctor. The results are shown in Table II.

TABLE II
RESULTS OF DIAGNOSING THE ABDOMINAL AORTA ANEURYSM IN MRI IMAGES

Input Image	Traditional Snakes		Proposed technique	
	Correct	False	Correct	False
Normal Abdominal Aorta (10 images)	8	2	9	1
Abdominal Aorta Aneurysm (10 images)	7	3	10	0
Total	15	5	19	1

IV. CONCLUSION

In this paper, we have designed a technique for diagnosing of abdominal aorta aneurysm in MRI images. The proposed technique is applied to synthetic images and aorta images. We also compare the proposed technique with traditional snakes model. From the first experimental results in segmenting of aorta images shows that our proposed technique very effective image segmentation performances and is better than the traditional snakes model on this particular problem. From the second experimental results in diagnosing of abdominal aorta aneurysm by Bayesian classifier shows that our proposed technique can diagnosis the abdominal aorta aneurysm are very close to the doctor opinions. It is able to provide more accurate results than 95%. A new approach has been successfully proved in a practical application. It can be believed that the proposed technique is a good approach for development in field of medical images processing.

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