An Automatic Segmentation Approach Towards the Objectification of Cyst Diagnosis in Periapical Dental Radiograph

Kavindra R. Jain[1,2(✉)] and Narendra C. Chauhan[3]

[1] RKU, Rajkot, India
[2] Department of Electronics and Communication, G H Patel College of Engineering and Technology, V.V.Nagar, Anand, India
kavindrajain@gcet.ac.in
[3] Department of Information and Technology, A D Patel College of Engineering and Technology, New V.V. Nagar, Anand, India

Abstract. The crucial part of image segmentation is the proper selection of initial contour to start with the efficient process. The main reason for such kind of segmentation is to reduce the human interaction and moreover to have more accurate results. In this paper we trying to objectify the cyst diagnosis problem in periapical images with the help of automatic segmentation. We have utilized the internal and external energy of image forces that pull it toward features such as lines and edges, confining them precisely. Scale space continuation can be used to develop the catch area encompassing a component.

Keywords: Computer vision · Snakes model · Cyst · Dental radiograph · Internal and external energy of image

1 Introduction

The rapid advancement in Computer Vision have had a vast change on dental radiography. Digital intraoral Radiography when introduced to dentistry, various studies were being done for reliability, reproducibility and for the purpose of validation. Low level task of grey scale dental radiograph like edge and line detection have been utilized as autonomous process. Marr [1] in his view told that higher level information is not collected so far to undergo the process comprising of what is contained in the picture. In this paper author tries to reduce the energy as a tool for diagnosing the cyst development in decayed tooth based on periapical dental radiograph. Due to various shades of grey color available lots of noise information from the dental periapical radiograph creates problem in segmentation of cyst from the gum portion. So we need to improve the efficiency of the technique used to segment the periapical dental radiograph.

In the past few decades image fragmentation based on computer analysis has increasingly played a crucial role in the field of medical imaging. The medical images available for analysis are either corrupted by noise or sampling artifacts. To address

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these challenges deformable models been widely utilized as a part of therapeutic picture division. Deformable models are fundamentally bends or surfaces characterized inside a picture area that can move affected by inward powers, which are characterized inside the bend or surface itself, and outer strengths which are characterized from the picture information. The inward powers are intended to keep the model smooth amid mis-shapening. The outside powers are characterized to move the model toward a protest limit or other sought elements inside a picture. Obliging removed limits to be smooth and fusing other earlier data about the question shape. Deformable models offer heartiness to both picture clamor and limit crevices and permit incorporating limit components into a rational and steady numerical depiction. The initialization of segmentation starts with adding suitable energy terms to the process of minimization, it is possible for a user to push the model out of a local minimum toward the desired solution. The result is an active model that falls into the desired solution when placed near it. M. Kass [2] firstly introduced the basic model of snake or active contours in 1987, which are curves defined within an image domain that can move under the influence of internal forces coming from within the curve itself and external forces computed from the image data.

The next section discusses about the basic mathematical description of snakes. Section 3 describes the energy terms that can make a snake attracted to different types of important static, monocular features such as edges, lines and contours. Section 4 concentrates on the suggested approach for the cyst identification in periapical dental radiographs. Section 5 simulates the results and Sect. 6 concludes the paper.

2 Basic Snake Behavior

The crucial snake model is a controlled congruity spline influenced by picture qualities and outside impediment powers. The internal spline forces to constrain a piece adroit smoothness impediment. The image powers highlights like lines, edges, and subjective structures. The external basic qualities are accountable for putting the snake near the pined for neighborhood minimum. These forces can, start from a UI, modified attentional instruments. The shape is depicted in the (x, y) plane of a picture as a parametric bend.

$$\mathrm{V}\ (\mathrm{s}) = (\mathrm{x}(\mathrm{s}),\ \mathrm{y}(\mathrm{s})) \tag{1}$$

Shape is said to take a vitality (Esnake) which is characterizes as the aggregate of three vitality terms.

$$E_{snake} = E_{\mathrm{internal}} + E_{external} + E_{constra\mathrm{int}} \tag{2}$$

The vitality terms are portrayed astutely in a way with the end goal that the last area of the form will have a base vitality (E min). Thusly our trouble of acquiring articles reductions to a vitality minimization trouble.

Internal Energy (E_{int})–Internal energy depends on the intrinsic property of the curve and addition of elastic energy and bending energy.

Elastic Energy ($E_{elastic}$)–The curve is care for as an elastic rubber band possessing elastic potential energy. It dispirit extending by introducing tension.

$$E_{elastic} = \frac{1}{2}\int_{s} \alpha(s)|v_s|^2 ds \tag{3}$$

where

$$v_s \equiv \frac{dv(s)}{ds} \tag{4}$$

Weight α(s) permits us to control elastic energy beside diverse parts of the contour. α basically utilized for reducing the size of region of interest.

Bending Energy ($E_{bending}$)–The snake is additionally considered to carry on like a thin metal strip offering ascend to bowing vitality. It is characterized as whole of squared bend of the shape.

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

Total internal energy of the snake can be defined as

$$\begin{aligned} E_{\text{int}} &= E_{elastic} + E_{bending} \\ &= \int_{s} \frac{1}{2}(\alpha|v_s|^2 + \beta|v_{ss}|^2) ds \end{aligned} \tag{6}$$

External energy of the contour (E_{ext})–It is obtained from the image. Characterize a capacity E image (x,y) with the goal that it acquire on its littler qualities at the components of intrigue, for example, limits

$$E_{ext} = \int_{s} E_{image}(v(s)) ds \tag{7}$$

The problem at hand is to find a contour v(s) that reduce the energy functional

$$E_{snake} = \int_{s} \frac{1}{2}(\alpha|v_s|^2 + \beta|v_{ss}|^2) ds + \int_{s} E_{image}(v(s)) ds \tag{8}$$

Using difference calculus and by concerning Euler-Lagrange differential equation we obtain following equation

$$\alpha v_s - \beta v_{ssss} - \nabla E_{image} = 0 \tag{9}$$

The contour deforms underneath the exploit of these forces. The improvement done in snake model for medical image segmentation is required for better objectification of cyst in intraoral dentistry. Hence the extraction of cyst in periapical images would be easier and much more accurate.

3 Active Contour Model

The basic theory behind active contour model lies on a curve whose behavior is going to be constrained by two aspects. The first and most important is due to the objective which is to perform a segmentation based on object and shape detection. So we need our contour to converge to the edges of the object we are interested in. The second constraint lies on the model of the contour we want to have. Due to the description we made before our contour function is going to be called $\gamma(s)$.

3.1 External Energy

The external energy is the component of our behavior function that describe how the deformable curve will match with objects of the image. To be attracted by a shape, we need to use a function that have the following properties: have at least one local minimum and be monotonic on areas around this point. To have such a function in an image we are going to use its gradient. We will enforce this behavior with a preprocessing consisting in a Gaussian Smoothing of the image to improve this aspect. So we can express the external energy function as:

$$E_{ext} = P(\gamma(s)) \tag{10}$$

Where P stands for a potential attraction field onto the edge of an object. So we have to consider this energy not only locally but for the whole contour C and to plug in the previous equation the properties we mentioned above. If the contour is closed we have:

$$E_{ext} = \oint_C \|\nabla I\|^2 (\gamma(s)) ds \tag{11}$$

Where I is representing the input image and ∇ is the spatial gradient function defined by:

$$\nabla I = \left(\frac{\partial I}{\partial x}, \frac{\partial I}{\partial y} \right) \tag{12}$$

Due to the fact that we want to minimize this energy, we are going to take the opposed value and introduce our Gaussian smoothing to enforce convergence to a local minimum. Using a weighting parameter on the external energy will allow us to increase the "visibility" of the gradient field by the snakes. So we can write it:

$$E_{ext} = -\delta \int_{A}^{B} \|\nabla(G_n * I\|^2(\gamma(s))ds \tag{13}$$

where δ is a real weighting value which for obvious reason would be positive and G_n is a Gaussian weighted kernel of dimension n.

3.2 Internal Energy

The internal energy is the component of the behavior function that describe the physical properties of our contour like smoothness or continuity and curvature. It is composed of two terms, the first one is describing the contour behavior regarding elasticity or smoothness. The second term is describing the curvature model of the curve and is function of the second derivative of our contour. If we put that into a mathematical form, we have:

$$E_{\text{int}} = f(\gamma'(s)) + g(\gamma''(s)) \tag{14}$$

The functions f and g are just going to be the Euclidean norm of the function. Then we need to specify that we want the energy for the whole curve C so not only for one spatial locations so we are going to sum this energy along the curve. Which will lead to two different cases. If our contour is closed:

$$E_{\text{int}} = \oint_{C} \|\gamma'(s)\|^2 + \|\gamma''(s)\|^2 ds \tag{15}$$

The previous definition is defining a model of smooth curve or function to describe the contour's behavior, which goes through the use of its derivative and in our case in their minimization. But, depending on the application and the choices of the user, the influence of these two aspects are not always equally important. So they need to be adjustable according to the situation.

3.3 Optimisation

Our goal in this section is to find the optimal parameters that will minimize the previous energy function we defined. This parameters are position vectors that will define the position of the snake which minimize this energy. Indeed we are looking for $\gamma(s) = (\gamma x, \gamma y)$ (s) such as E_{snake} is minimal. The optimization formulation of our problem is then:

$$s_{optimal} = \arg\min_{\gamma \in F} E(\gamma(s)) \tag{16}$$

Which means that we want to find the value of s which is the argument that makes the curve γ, of the set of possible curve, of minimal value regarding the energy function E.

3.4 Gaussian Smoothening

An important part of the set up to perform a segmentation using active contour is to preprocess the image using a Gaussian filtering. If our input image has a good quality, its edges are going to be extremely well defined, which means that there are going to be abrupt. In fact, we need to attract progressively the snake to the edge of the object, so we need to "attract" it. To do that we need to "spread" the edges around to create a more smoothed gradient around the edge. Another reason of applying a Gaussian filtering is regarding the noise issue.

3.5 Kernel Settings

The kernel size and type is really important as we mentioned before because it influences the way the edge is spread around. It also as a consequence of our simple convolution implementation reduce the size of the resulting image. This aspect can of course be noticed while looking at the intensity curve of the smoothed image where we can clearly see null areas on the sides of the intensity curve.

3.6 Contour Construction

As we said before, we are going to rely on the user to define an initial shape around the object that will serve as an initialization set up.

3.7 Stopping Criterion

In the original method presented by Kass et al. It seems to have no indications about a stopping criterion on the snake's evolution. When using the greedy method we have two stopping criterion. The first one is if the number of points that move at each iterations fall under a certain threshold value. The other one being that the number of iterations reaches another threshold value. Indeed, if we initialize the contour too far from the shape with a small kernel and a too low iteration threshold the algorithm will fail in reaching the shape. On the other hand if we have a too large number of iterations and a too close initialization we will spend time looking a contour that oscillate in the edge origin without significant improvements. This is maybe where the criterion can become useful.

4 Suggested Approach

The suggested approach is followed by below steps:

- Collection of periapical database images comprising of cyst diseases.
- Fix all the values of parameters so described in snakes model
- Initialize the contour by clicking at a sequence of points close to the object to be segmented, the contour is then defined as the set of consecutive points.
- Design a stopping criteria for the iterative process.
- Choose different initializations for starting contour, also with the different number of control points, and observe the evolution of the deformable contour.

After completing above procedure, we find out the edge of the affected part using canny afterward we measure the area of that part. For severity measurement, geometrical and textural features must be analyzed (Figs. 1, 2, 3 and 4).

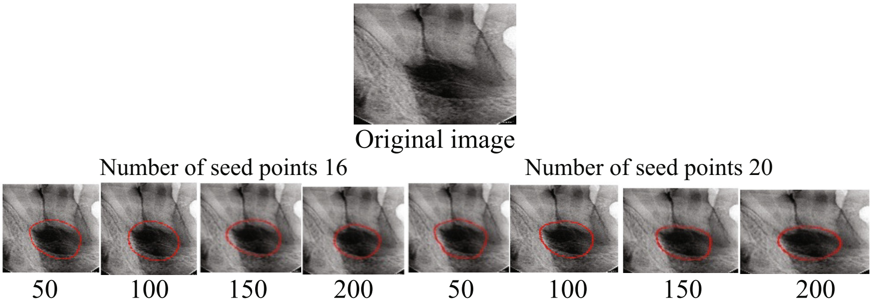

Fig. 1. Cyst identification of test 1 (patient 1) with various iterations and selected number of points

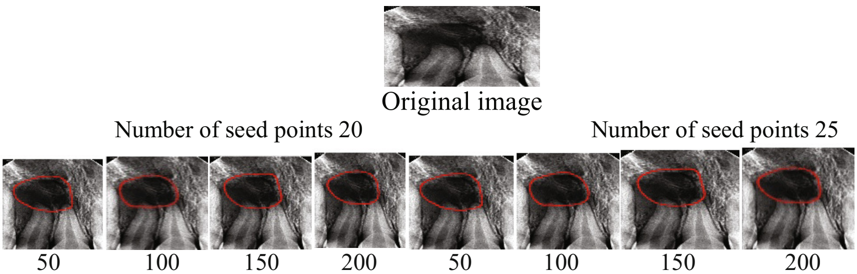

Fig. 2. Cyst identification of test 2 (patient 2) with various iterations and selected number of points

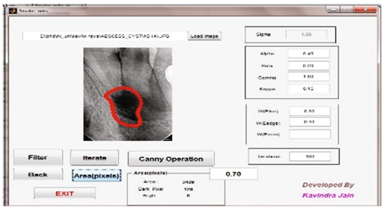

Fig. 3. Cyst identification of test 1 (patient 1) with various iterations and selected number of points (A GUI)

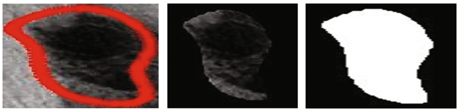

Fig. 4. Cyst identification of test 1 (patient 1) with filtering and final binaries detected output of resultant image

5 Result and Discussion

As described in Sect. 4 we have run the code on various database images and their results will be attached here. In this, various parameters α,β,γ, $W(E_{line})$, $W(E_{edge})$, $W(E_{term})$ are utilized for getting affected area of disease on various database images as shown in Table 1.

Table 1. Parameters and values for different patients and test images based on snakes model

Parameter	α (alpha)	β (beta)	γ (gamma)	k (kappa)	$W(E_{line})$
Values	0.4	0.2	1.0	0.15	0.3

6 Conclusion

We implemented GUI (Graphical User Interface) in MATLAB. In this GUI, we added some features like area, canny. This user friendly approach was quite satisfactory in providing a broad idea to doctor as well as patient for a precancerous treatment. As this tool has all the add-on to give a broad descriptive area of the affected patient with

The importance of the medical image in healthcare is constantly growing, making healthcare more effective and patient friendly. With innovative imaging technologies diseases can be detected earlier and more precisely: more useful for both patient and doctors.

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