Active Contour Model based Segmentation of Colposcopy Images from Cervix Uteri using Gaussian Pyramids

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Abstract

A new segmentation algorithm based on an active contour model at multiple scales, using the Gaussian Pyramid is performed on colposcopic images. The segmentation outlines a specific feature from the cervical images - the Transformation Zone. A new snake - the boundary-searching snake, based on both image gradient features and region features is implemented, starting from the low image resolution level, aiming to avoid a specific artifact in the images-known as a specular reflection. Further, the snake coordinates are propagated to the highest level of the GP, segmenting one of the most complex and variable anatomical shapes -the cervix uteri.

1. Introduction

Colposcopic images provide a visual exploration of the uterine cervix for diagnostic purposes. Currently, colposcopic images are considered as an adjunct to the clinically established Pap smear test for diagnosis of cervical cancer. The Pap smear test is unable to achieve a concurrently high sensitivity and high specificity [1]. Its purpose is to lower the so named "false-negative" finding of abnormal cervixes and to facilitate taking the Pap smear and biopsy procedures for the physician in charge. The most prominent area where cervical neoplasia can occur is the area around the endocervical canal or cervical canal os, named transformation zone (TZ). This is where two types of tissue are subjected to usually normal process of reversible tissue metaplasia-the squamous epithelium – SE, (known as epithelial tissue) transforms to columnar epithelium and vice versa. The difficulties of evaluation of the TZ are that sometimes this specific area within the normal cervix is hardly classified by inexperienced physician. Also, some of the visibly "normal" TZs can be discovered as pre-cancerous only after a histology test. Therefore, a physician can be guided by a segmentation procedure, to ensure that the test or the biopsy is taken from the right area of the cervix.

The TZ if often seen as darker area with rugged edges with no specific shape most often enclosing the cervical os, surrounded by usually smooth and pinkish cervical epithelium.

As the cervix is an internal organ, it is always moist, therefore, the specular reflection yields "white" spots on the image, that consist of the light spectrum of incident light. On the image, it creates small areas of high gradients, that ought to be avoided, when a deformable model as a snake is implemented.

This paper presents a novel method of active contour models, based on both gradient forces and the forces derived from the statistics of the enclosed region.

Active contour models (ACMs) or snakes, were first proposed by Kass et al. [2], are good candidates for segmentation of medical images where the target boundaries are difficult to separate. Algorithms based only on a simple image feature as edges or thresholds are not efficient. In the current paper, a snake, akin to a mechanical elastic body is forced to "adapt" to image step edges and gradients, as the smoothed image gradient and the local statistical features as mean pixel value and the local standard deviation are taken into account. An operator on an automatically cropped image initializes the snake. Further, a smoothing separable gaussian filter is applied and four level GP is performed. The snake starts to "search" for the target boundary from the lowest level from the Gaussian Pyramids, working its way over the smoothed and lower resolution image, avoiding the traps created by the specular reflection.

When the snakes energy reaches a local minimum, the snake propagadation stops and the pixels' coordinates which belong to the snake at that particular level are rescaled to the next level, and becomes an initial contour for the snake at the higher level and so forth. At the highest level, the boundary of question is finalized.

Currently, the task of evaluating colposcopic images is performed only by a trained expert evaluator in USA, or specialist gynecologist in Europe. The general practitioners and midwifes need specific training for that specialized task, which is not yet available in medical schools. Therefore, a snake is an important boundary searching technique for colposcopic images.

The remainder of this paper is organized as follows: Section 2 talks about the searching strategy, which is the main contribution of this paper. Section 3 presents a multiresolution approach using a Gausian Pyramid. Experimental results for both synthetic and natural images are presented in Section 4. Section 5 discusses problems with the presented method and outlines future work.

2. Snakes

The snake is an analogy to a mechanical system; influencing forces can be represented by equivalent potential and kinetic energy. It can be represented as a time varying parametric contour

$v(s,t) = (x(s,t), y(s,t))$,

in the image plane $(x,y) \in \Re^2$, where x and y are coordinate functions of the parameter s $s \in [0, L]$ and $\boldsymbol{t}$ is time, as described in [5]. The shape of the contour subject to an image $I(x,y)$ is indicated by an energy functional:

$$E(v)=S(v)+P(v) \qquad (1)$$

The first term is the internal deformation energy is defined as:

$$S(v) = \frac{1}{2}\int_0^L \left(\alpha(s)\left|\frac{\partial v}{\partial s}\right|^2 + \beta(s)\left|\frac{\partial^2 v}{\partial s^2}\right|^2 \right) ds \qquad (2),$$

where $\alpha(s)$ controls the "tension" of the contour and $\beta(s)$ regulates the 'rigidity" and L is the length of the contour.

The second term in (1) is the external image energy, or the previously mentioned potential energy, known as the gradient of the image potential function, where $P_I(v(s))$ is a gradient operator and $n(v(s))$ is the vector, normal to the current contour.

$$P(v) = -\int_0^L n(v(s)).P_I(v)ds \qquad (3).$$

These are the gradient based snakes or traditional snakes, implemented by Kaas et al.[2], who used discretized Euler differential equation to minimize the energy in equation (1), locally using the steepest descent algorithm. As it was pointed out before, the specular reflection creates a local minima, and the gradient based snakes as implemented by Leymarie and Levine [3], Radeva and Marti [4] can easily trapped by this local minima.

In the current implementation a region based snakes feature is included within the energy temporal propagadation of the snake. Region based snakes are described in details in the work of J. Liang *et al.* [5], Ronfrad R.[6], J. Wang [7] and Metaxas D. [8]. Region's energy is an estimate of the statistics of the region within the contour or topology specific for the region. In the experiment the strategy is to include a region based functional, based on the mean pixel's value $\mu_{v(s)}$, the local variance $\sigma_{v(s)}$ within the contour $v(s,t_i) = (x(s,t_i), y(s,t_i))$, where i is a time step.

Therefore, the energy equation for the snake can be written as:

$$E = E_{\text{int}} + E_{region} + E_{potential} \qquad (4),$$

where E_{int} is the equation (2), and can be written as:

$$E_{\text{int}}(v(s)) = (\alpha(s)\,|\,v_s(s)\,|^2 + \beta(s)\,|\,v_{ss}(s)\,|^2) \qquad (5),$$

where the regional energy is:

$$E_{region}(v(s)) = -\left|\frac{v(s+1)+v(s)-2k\mu}{2k\sigma}\right| \qquad (6),$$

where k is a constant, 2 or 3, μ is the mean intensity and σ is the standard deviation from the seeded region. The term $\frac{v(s+1)+v(s)}{2}$ is the average intensity value between a current snaxel (snaxel can be defined as snake's element, similar to pixel) and its two neighbors.

The last term of the energy equation represents the external or the potential energy derived from the gradient of the image preprocessed with Gaussian low pass filter with a standard deviation σ and gradient operator ∇:

$$E_{potential} = -\nabla\left|(I(x,y) * G_\sigma(x,y))\right|^2 \qquad (7)$$

The two dimensional Gaussian filter $G_\sigma(x,y)$ is executed as two separable one-dimensional filters in order to reduce the computational cost. The potential or external energy from the gray scale image is designed to lead the snake toward the step edges.

The equation minimizing the energy E (4) is:

$$\alpha(s)\,|\,v_s(s)\,|^2 + \beta(s)\,|\,v_{ss}(s)\,|^2 \;.... \\ -\left|\frac{v(s+1)+v(s)-2k\mu}{2k\sigma}\right| - .. \\ -\nabla\left|(I(x,y) * G_\sigma(x,y))\right|^2 = 0 \qquad (8)$$

A solution to (8) involves a dynamic or temporal function of the snake $\mathbf{x}_t(s,t)$, which treats $\mathbf{x}_t$ as a function of time. The snake uses 5 nodes (the central node as current and two predecessors and two successors) at a time to evaluate the tensile forces, flexural forces, and the inflating forces within the equation for the internal energy. The internal energy formulation is similar to the formulation proposed in the Wang J. *et. al* [7] and Gunn and Nixon [9], where the snaxels are parameterized to keep the snake inflated and snake to change only if the internal values of the curvature of the polygon, exceeds pre-defined constrains. The detailed explanation of the constrains and conditions of the internal energy formulation can be found in [7] and [10]. The external forces strength is updated each time after the spatial step and the energy is evaluated, using iterative approach.

The colposcopic images are truecolour RGB images. A typical RGB image of a cervix is shown on Figure 1. The TZ visible on the image (Figure 1.) if often seen as darker area (visible as a central part of the image) with rugged edges with no specific shape most often enclosing the cervical os, surrounded by usually smooth and pinkish cervical epithelium. The white reflective “spots”are from the specular reflection with high pixel values and high gradient.

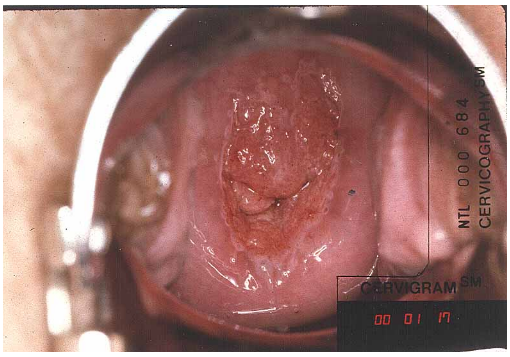

Figure.1. Digitied colposcopic RGB image of normal cervix uteri.

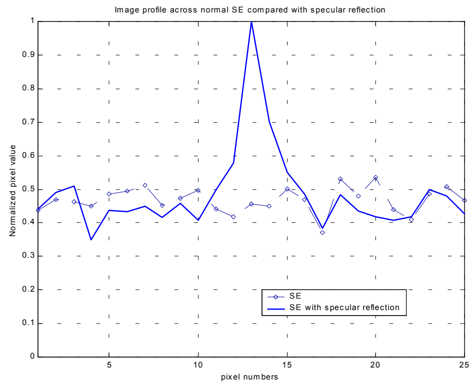

Figure 2. The representation of an image profile across the SE (dashed) and SE with specular reflection (solid) with high peak in the middle.

The Figure 2. Shows the gray scale image profile form the SE which is relativley smooth and the SE with rapid intensity changes creating the high gradient.

The implementation of the snake is shown on the Control Flow Chart, presented on Figure3.

The snake initialization is performed on lowest level of the GP, reducing the gradients of the specular reflection edges and reducing the computational cost.

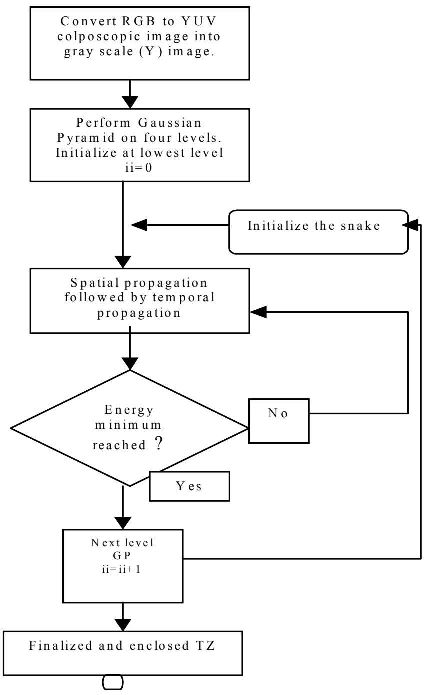

Figure 3. Control Flow Chart on the processes of the implementation of the snake.

This is followed by snake iterative re-parameterization until an energy minimum is reached. The coordinates of the snake are passed to the upper level of the GP until the final contour enclosing the TZ is found.

3. Gaussian Pyramid

The idea of a multiscale approach to snakes, corresponding at different level of resolution seems appealing, because the main factors that affect the performance of the active contours are that of noise, and in the colposcopy images, the specular reflection from the soft tissue is added to the noise. Preprocessing with median filter or a gray-scale morphological filter, does not improve the performance of the snake and as the operators are non-linear, some of the important image information could be lost. The specular reflection forces the snake to run and fit around the reflection, which has the strongest gradient in the area. Also noise and other artifacts can ‘trick’ the snake to diverge from the correct solution.

One approach is to use a GP for multiresolution processing of the images. Although the translation of the edges effect can be seen, the GP pre-processing allows the snake to work on lower resolution image, which speeds up the parameterization of the snake.

Let $M_0(m,n)$ is the initial image and m=0,……Q-1, n=0,….P-1, $P = p\times 2^K, Q = q\times 2^K, p$, q, and K being positive integers. The GP, of which k indentifies the level and K>0 the $(p\times q)$ -sized top level or root, is defined as

$$M_k(m,n) \equiv \sum_{i=-Lr}^{Lr}\sum_{j=-Lr}^{Lr} r(i)\times r(j) M_{k-1}(2m+i,2n+j) \qquad (9)$$

for k=1,….,K, m=0,…..P/2^K -1, n=0,….Q/2^K -1. The solution for the multiscale approach is: given a decreasing sequence $\{\sigma_1,\sigma_2.......\sigma_k\}$, the corresponding filtered gradient images $M_k = |\nabla(I(x,y) * G_{\sigma k})|$,for $k=1,....K$. Using $M_{i-1}, i\in\{2,...k\}$, one obtains an approximate solution for the snake for the next scale and so forth, reaching the original size image. Figure 4. a) shows the Gaussian Pyramid representation of a gray scale intensity image, generated at four levels. The image set from Figure 4 b) is a GP representation of a gray scale image, weighted in such a way, that a bigger weigh is given to the green and the blue channels from the original RGB truecolour image, compared to the weight of the red channel from the RGB image. This is done to enhance the TZ. This particular preprocessing is based on findings in [13], where a detailed description of the spectral scattering properties of the different types of cervical tissue is discussed.

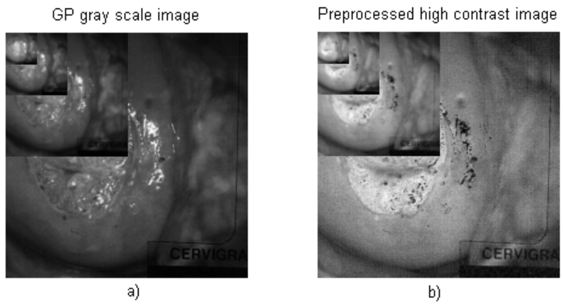

Figure 4. Pyramid representation of image set: **a)** the smoothed original gray scale image **b)** the preprocessed gray scale image with emphasis on the green channel

4. Experimental Results

4.1. Experiments with synthetic images

The first experiment was performed to test the robustness of the snake with respect to noise on synthetic test images. A synthetic bi-level image $B(x,y)$ was created as shown on Figure 5a). The test region of interest was formed by a polygon, filled with ones and the background, filled with zeroes. The area with ones was used as a “mask” of a the synthetic image $S(x,y)$. The synthetic test image is a function of the gray scale colposcopic image $I(x,y)$ nd the bi-level image $B(x,y)$ with an impulsive additive noise $N(x,y)$. The synthetic test image is formed as:

$$S(x_i,y_j) = B(x_i,y_j).I(x_i,y_i) + N(x_i,y_i) \qquad (10)$$

Where $i=1,2...r$ and $j=1,2...c$, r and c are the number rows and columns in the images.

The noise level is measured as the percentage of randomly chosen pixels that change their value from 0 and 1 and vice versa. The image is shown in Figure 5d) is the fully formed synthetic image $S(x,y)$. The initial contour of the snake is shown on Figure 5 c). The final position of the snake on the last level of the GP is shown on Figure 5d). The typical numbers of iterations across the three levels, starting from the one level above the root level are 10 –20 iterations altogether. The snake shows robustness to a noise at around 25% noise. The typical coefficients for tensile forces are close to 2, and the coefficients of the flexural forces are a negative fraction of one.

Although the algorithm follows the constraints of the previously described dynamical system in Section 2, in its current form, the selection of the parameters values are based on the empirical observations, which it seems are to be most widely used strategy [14]. Further aim of the snake algorithm development is possible automatic selection of the parameter values.

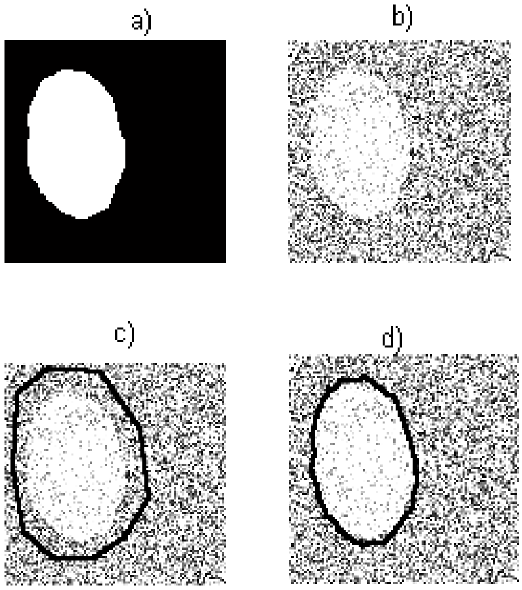

Figure 5.a) A bi-level image used as a mask **b)** A synthetic image, composed of additive noise and masked gray scale colposcopic image, simulating a TZ **c)** initial contour of a snake **d)** final contour of the snake

4.2. Experiments with colposcopic images

The experiments with preprocessed colposcopic images are performed using Matlab based functions for its discrete implementation. The snake was initialized on the image from GP, that is one level above the root level, because the root image was too small to visualize - [25 x 25] pixels. The initialization was followed by temporal and spatial snake development using a recursive procedure. The initial snake contour is shown on Figure 6.a).

The Figure b) shows a developed snake at the next level after 3 iterations. It illustrates that the “spring” and the gradient forces “pulled” the snake toward the TZ. The Figure 6 d) gives the final result of the snake, fully enclosing the TZ.

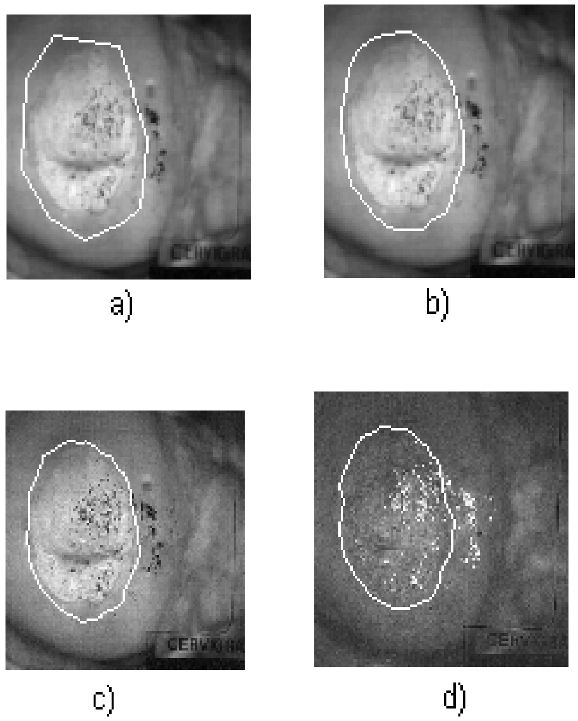

Figure 6 The energy minimization process: **a)** the initial contour **b)** snake at low resolution level **c)** snake at higher resolution level the snake in b) is an initial “guess” for the current snake **d)** TZ enclosed by the snake

The snake performance is still dependent on the local maxima from the image. The high gradient local values, yielded from the specular reflection, although smoothed from the filtering, still have important contribution as a local potential energy maximum. The performance of the snake depends of the preprocessing the image, which can be researched further.

The multiscale-based snake improves the performance of the ordinary snake, because at each level, the initialization of the snake is based on inferences, executed from the level below.

The translation of the edges effect, introduced by the low-pass Gaussian filter from the Gaussian Pyramid often contributes to the mislocalisation of the boundary.

The evaluation of the mislocalization of the boundaries, compared with human performance can be studied further.

5. Summary

The snake, described in the current paper can automatically converge and enclose a important anatomical feature from colposcopic images. This will lead to an automation of the procedure of taking a biopsy or Pap smear test from the right area of the cervix. Further improvement of the performance of the snake that can be made, is to make the initialization of the snake without an operator or user-intervention., possibly by identifying a feature as the cervical os as an initial snake region.

The implemented snake is one step further toward a semiautomatic segmentation of the colposcopic images from the cervix.

As the currently described snake is successful, its performance can be improved at the initial stage of the process: the preprocessing of the image. As the cervix uteri are internal organ with a specific conical shape, the image has uneven illumination. Therefore, a further strategies to improve the performance of the snake is to use images with uniformly distributed illumination, or introduce a geometric transformation as preprocessing of the image.

6. References

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