ACTIVE CONTOUR MODELS - A MULTISCALE IMPLEMENTATION FOR ANATOMICAL FEATURE DELINEATION IN CERVICAL IMAGES

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ABSTRACT

In the work presented here, digital colposcopic images from cervix uteri are subjected to a segmentation algorithm using active contour models at multiresolution levels, on images formed by a Gaussian Pyramid (GP). The segmentation aims to outline a specific feature from the cervical images - the Transformation Zone (TZ), where a possible neoplasia can occur. The process includes an implementation of a boundary-searching snake, based on both image gradient features and region features. The adaptive "snake" initially is executed on the image with the lowest resolution from the GP, aiming to avoid a specific artefact in these images, known as specular reflection (SR). Further, the snake coordinates are propagated to the image with highest resolution from the GP. Under a specific set of parameters, we achieved accurate delineation of the TZ, measured by comparison with pre-defined "ground truth".

1. MOTIVATION FOR THE MULTILEVEL SNAKE APPLICATION IN CERVICAL IMAGES

Accurate and automatic segmentation in computer aided diagnosis is one of the final goals in digital colposcopy systems. Colposcopy provides visual exploration of the uterine cervix for diagnostic purposes. Colposcopic impressions are adjunct to the Pap smear test to stage and diagnose cervical cancer precursors. Digital colposcopy might be *the only alternative* as cervical cancer screening in developing countries, where 80% of the women's world population live, where the cytology tests are practically unavailable or expensive. On other hand, the Pap smear has many errors and various sensitivity and specificity limitations [1].

The anatomical area surrounding the endocervical canal is the transformation zone (TZ), where possible neoplasia occurs in 90% of the cases. TZ is the target area to obtain samples for cytology test (close to x10^6cells per slide). The normal TZ has subtle features and often it is hard to distinguish. Thus, a computer aid for delineation of the TZ can be a valuable tool for the primary step of the Pap test procedure obtaining the right cells from the cervix for visual diagnostics. The TZ is often seen as a slightly textured area, enclosing the cervical canal (os), surrounded by the pinkish smooth epithelium.

Colposcopy images are endoscopic type of images, so their illumination conditions yield challenging artifacts. A prominent one is the strong light reflected from the moist epithelium surface, known as specular reflection (SR),visible as high-intensity light spots with strong edges that have high gradients. The cavity located cervix also results with uneven image illumination, due to the non-planar surface reflectance.

The presented method is tailored to decrease the impact from the two concerning issues, adopting a multiscale approach for implementation of an active contour model (aka "snake"), including a region-based feature in the energy equation of the snake and represents an adaptive approach to the problem. No previously published *adaptive signal processing* algorithms to outline the TZ are known to exists. The goal is to extract the boundaries of the TZ, assumed to be relatively homogenous region. The snake minimize the total energy of the adaptive contour, counterparting the energy of the region, as in equation (1). This equation (1) exploits the slightly textural signature of the region,included as an expression of its functional dependency on the first and the second statistical moments, intrinsic to the area of the enclosure. The advantage of this method is that it does not use any "a-priori" information for the region. We estimate the region's property measures while the snake "develops". We calculate region's measures not only during snake's initialization, but at any level of the pyramid for the spatial and temporal development of the snake, starting from the lowest resolution and propagating to the levels with the highest resolution with finer image details.

In the paper we introduce the equations of the active contour models in Section 2. In Section 3, we describe the region-specific snake and we discuss its implementation using Gaussian Pyramid. In experimental Section 4 we justify the test of the snake on synthetic images and report the results of the evaluation. We discuss the experimental ap-

0-7803-8554-3/04/$20.00

proach and its value and accuracy in Section 5.

2. ACTIVE CONTOUR MODELS (SNAKES)

The snake is an analogy to a mechanical system; its 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 set $s \in [0,l]$ and t is a time axis [2]. Each discrete element of the contour is usually named "snaxel", similar to "pixel". If the condition of the equality: $v(0,t) = v(l,t))$ exists, the shape of the contour is a closed one (l is the length of the contour) and the active model can be presented by the energy functional:

$$E(v) = S(v) + P(v) \tag{1}$$

The first term of the the total energy $E(v(s))$ is the internal deformation energy $S(v(s))$ and it is defined as:

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

where $\alpha(s)$ controls the tension of the contour, $\beta(s)$ regulates the rigidity at an exact moment in time.The second term in the energy equation (1) represents the external energy $P(v(s))$, utilizing the gradient forces $P_I(v(s))$ in the image $I(x,y)$ and the vector $\mathbf{n}(v(s))$, normal to the current contour:

$$P(v) = -\int_0^l \mathbf{n}(v(s)).P_I(v(s))ds. \tag{3}$$

The snakes with the energy balance as in (1) are gradient-based snakes, first implemented by Kaas et al. [2], and they are governed by minimization of the energy $E(v(s))$ balance, satisfying the discrete Euler - Lagrange equation that can simply be written as: $\mathbf{S} + \mathbf{P} = 0$, which is used in [2], [3] and [4] and elsewhere. The "ground state" initial model described in [4], uses equation (3) and it is another type of gradient-based snake. We include equation (3) in our current model as well. The snakes using only gradient forces have several drawbacks and the one most significant for our application is that the contours can be easily "trapped" within the edge gradient with high intensities. Another drawback is that the spatial process of contour development in the gradient - based snakes is not robust against the noise, especially the impulse noise presented in the image.

The second major type of snakes are the region-based snakes. The region based snakes use specific feature(s) of the region, and their mathematical description is included in the energy of the region enclosed by the contour. The feature, for example, can be a specific shape descriptor, acquired "a-priori", as the contrast or difference between the enclosing area and the background or known statistical estimate. Ideally, in our case, for the implementation of our active contour, we take into account the gradient of the image in the energy equation, combining it with an statistical estimate of the TZ region. As the region contains texture, a possible mathematical expression for the features can be the estimates of the local mean value $\mu_{v(s),}$ or the local variance $\sigma_{v(s)}$ of the enclosed region, or both. Therefore, a combination of region-based snake and a gradient-based snake is a good candidate for segmentation of the cervical images (Fig 1. on the left) where the target boundaries are difficult to separate, the specular reflection and uneven illumination is an issue, there are possibilities of noise, because of the clinical environment of the colposcopy or digital cervicography.

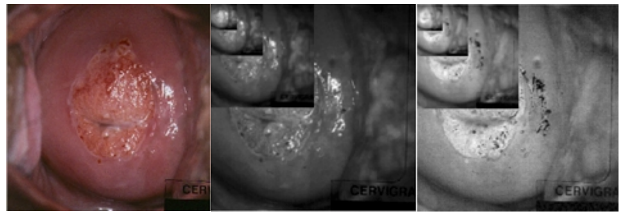

Fig. 1. Left: image from a normal cervix with centrally located os and surrounding TZ with prominent SR; Middle: four consecutive levels of Gaussian Pyramid in the inserts, the smallest image in the upper left represents the highest level of the pyramid; Right: gray images on different pyramid levels with an enhancement of the green channel;

3. METHOD OF IMPLEMENTATION

In our experimental method we include a region-based dependent functional, using the mean pixel value $\mu_{v(s)}$, updated constantly via integration within the enclosed regular polygon (based on the Green's theorem) for the discrete case of the digitized image. Calculation of the local variance $\sigma^2_{v(s)}$ for the discrete implementation of the contour $v(s,t_i) = (x(s,t_i), y(s,t_i))$ is also included in the equation of the total energy and this is performed "on the fly," during the snake's development, because of the TZ texture content, compared to the smooth surrounding tissue of squamous epithelium. The local variance is used as a nonstructural texture measure for the region of interest. The total energy equation for the snake at level j of the pyramid can be written as:

$$E_j^{tot}(v(s,t_i)) = E_j^{int}(v(s,t_i)) + E_j^{region}(v(s,t_i)) + E_j^{pot}(v(s,t_i)), \quad (4)$$

where E_j^{int} is detailed in (2) and also is known as:

$$E_j^{int}(v(s,t_i)) = \alpha(s)\left|\frac{\partial v}{\partial t_i}\right|^2 + \beta(s)\left|\frac{\partial^2 v}{\partial t_i^2}\right|^2 \quad (5)$$

The regional energy is:

$$E_j^{region}(v(s,t_i)) = -\left|\frac{\overline{v}(s,t_i) - 2\rho\mu_{v(s,t_i)}}{\rho\sigma_{v(s,t_i)}}\right| \quad (6)$$

where $\overline{v}(s,t_i)$ is the average intensity value of a current snaxel and its two neighbors and ρ is a coefficient between 2 and 3.

The last term of the energy equation $E_j^{pot}(v(s,t_i))$ represents the external energy, derived from the gradient of the image, pre-processed with Gaussian low pass filter $G_\xi(x,y)$ with a spatial standard deviation ξ and a gradient operator ∇:

$$E_j^{pot}(v(s,t_i)) = -\gamma\nabla|G_\xi(x,y) * I(x,y)|^2 \quad (7)$$

For the choice of ξ (standard deviation of the Gaussian filter $G_\xi(x,y)$), we express certain considerations accounting for the frequency content of the image. These considerations are beyond the scope of this discussion, but ξ was chosen to contemplate a “trade-off” between the unnecessary noise-related steep edges’ gradients and to preserve the fine and important details of the image, such as the sharpness of the TZ margins, cervical canal or vascularity details.

3.1. Multilevel Snake

The solution to $E_j^{tot}(v(s,t_i)) = 0$ is a dynamic function of time t_i at each development stage i of the local contour. The contour is evolving at each stage j of a multiresolution pyramid. When the contour comes to an intermediate ”steady state” on j^{th} level of the Gaussian Pyramid (the condition for ”steady state” is: $\frac{\partial v(s,t)}{\partial t} = \frac{\partial^2 v(s,t)}{\partial^2 t} = 0$), the snake ”translates” its coordinates from the upper to the lower pyramid level via multiresolution pyramid linkage [5]. The snake uses five nodes at a time (central, two predecessors and two successors) to estimate the total balance of the tensile, flexible and inflating forces within the internal energy equation. Further, the snaxels are re-parameterized to keep the snake inflated, to “resists” the shrinking effect, and to ensure that the “resistance” is invariant to scale, translation and rotation [6]. The strength of the external forces are updated each time, and the total energy is evaluated via an iterative approach.The graphical description of the process flow for the snake formation on several pyramid levels is shown on Fig.2.

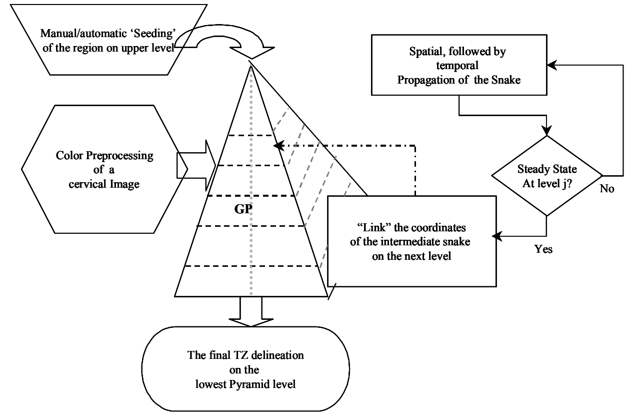

Fig. 2. Flow chart of the process of snake implementation on different pyramid levels. The initialization of the snake starts on the highest level. After the snake reaches a “steady state” on j-th level, the coordinates or the contour are linked to the lower level.

We start the initialization of the snake on the uppermost level of the Gaussian Pyramid, where the image is smoothed the most and the strength of the SR gradients are diminished,thus simultaneously reducing the computational cost and avoiding unnecessary “traps”. Although there is always an “edge translation” effect, due to the smoothing operation, the GP pre-processing allows the snake to work on a lower resolution images, which speeds up the parametrization of the snake.

3.2. Gaussian Pyramid

The Gaussian Pyramid is a multiresolution image representation obtained trough a recursive reduction, i.e. low-pass filtering and subsampling of the discrete image $I(m,n)$. Let the discrete image $I_0(m,n)$ be the input image, $m = 0,1,2...(Q-1)$, and $n = 0,1,2...(P-1)$, where $Q = 2^k q$, and $P = 2^k p$, where p, q, K are non negative integers. The GP on the top level has an image of size $p \times q$ pixels and on the k^{th} th level $I_k(m,n)$ can be identified such as:

$$I_k(m,n) = \sum_{\epsilon=-L}^{L}\sum_{\varepsilon=-L}^{L}[r(\epsilon)\times r(\varepsilon)]I_{k-1}(2m+\epsilon, 2n+\varepsilon) \quad (8)$$

where the 2-D reduction filter is given as the outer product of a linear symmetric separable kernel $\{r(\epsilon,\varepsilon)\}$, with size in one dimension $2L+1$. The Gaussian filter $G_\zeta(\epsilon,\varepsilon)$ has a cutoff frequency ω_{cutoff} in the interval $(0.35\pi, 0.45\pi)$, where π is considered to be the limit of the frequency scale for the discrete image $I_0(m,n)$ in one dimension. The cutoff frequency is selected to form a good trade off between preserving the details of the image and achieving the per-

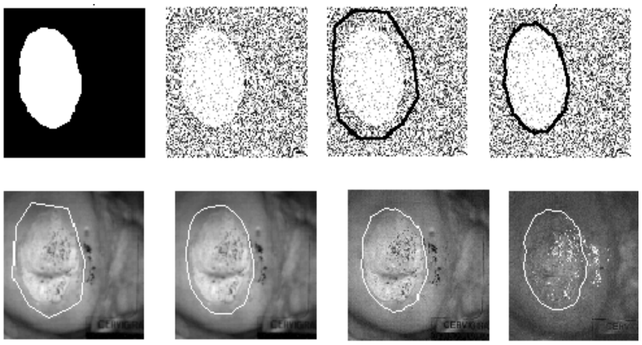

Fig. 3. Upper row from left to right: representation of the "ground truth," the initial test on the synthetic image, an intermediate test snake, final snake on synthetic image.Lower row from left to right: The initial stage of the snake, two of the intermediate steps in the snake development, last stage of the snake on lower level of GP.

fect aliasing rejection, caused by the subsampling procedure ($\downarrow 2$, at least for its upper boundary: $\omega_{cutoff} \equiv \frac{\pi}{2}$, to avoid aliasing).

4. EXPERIMENTAL RESULTS

We performed simulation experiments of the snake development on synthetic images (Fig. 3.Upper row). The synthetic images represent a simplified model of the "ground truth", where the area of the TZ contained "ones" and the TZ complementary - "zeros". To test for the robustness against noise we added 25% pseudo random noise.

The experiments with preprocessed colposcopic images, 512×512 pixels resolution (87 gray scale images using a chrominance of the YUV color transform) were performed using Matlab5.1, each one with three different initializations. The snake was initialized on the image one level above the root level on an image 50x50 pixels. The initialization was followed by temporal and spatial snake development using a recursive procedure. The initial snake contour is shown on lower row of Fig.3. and the images on the left represent an already developed snake at the next level than after about 15 iterations, until it reaches a "steady state".The figures illustrate the role of the "spring" and the gradient forces under the minimization algorithm enclosing the contour toward the TZ.

Although, that we estimated that the accuracy of delineation of TZ reaches the average value close to 91% by comparison to the "ground-truth" set by black and white "masks" (Fig.3. Upper level, far left), the snake's performance depends on the choice of the set of parameters, such as the coefficients $\alpha\left(s\right), \beta\left(s\right)$, and ρ, and also on the local maxima from the image. In addition, the algorithm is not fully automatic as it requires manual initialization by an operator. The high gradient local values, yielded from the specular reflection, although smoothed from the filtering, still make an important contribution as a local potential energy maximum and if the set of the coefficients α, β and ρ have large variation from the set of values mentioned above, the snake does not converge and needs more iteration to reach a steady state. In addition, the multiscale-based snake improves the performance of the ordinary snake, because at each level, the initialization of the snake is based on a contour closer to the targeted one, "linked" from the lower resolution level to higher detail level one.

5. SUMMARY AND CONCLUSIONS

The snake, described in the current paper encloses an important anatomical feature such as TZ. This can guide and aid the procedure of taking a biopsy, Pap smear test from the right area of the cervix or in the future, to delineate a suspicious area on the cervix. Algorithm-wise, our goal is to improve the parameter condition for this particular snake and to suggest a method for full automation avoiding the intervention from an operator, possibly using feature modelling in color space.The implemented snake is one step further toward a semiautomatic segmentation of the colposcopic images from the cervix and includes multiscale approach.

6. REFERENCES

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