Advanced Materials Research *Online: 2011-09-27*
ISSN: 1662-8985, Vols. 341-342, pp 714-719
doi:10.4028/www.scientific.net/AMR.341-342.714

A Novel Approach for Color Tongue Image Fast Segmentation Based on Level Sets

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Keywords: Color Tongue Image Segmentation; Level Sets; Variable Time Step

Abstract. To make variational level set method applicable to the application of tongue segmentation, this article introduced a kind of color tongue image fast segmentation method based on level sets. The early variational level set method is improved from the following aspects: the boundary feature weight function is improved to make this method adaptable to color tongue image segmentation, and a kind of variable time step method is introduced to increase the efficiency and accuracy of segmentation. As the comparison experiment results show, our method is about 1 time faster than the early method, and its accuracy is higher than the early one.

Introduction

Tongue diagnosis is an important content of observation, auscultation and olfaction, and interrogation and palpation in TCM(Traditional Chinese Medicine). Traditional tongue diagnosis mainly depends on observations to features of tongue substance and tongue coating by Chinese doctors. The result of tongue diagnosis is quite subjective.

In 1990s, some researchers began to use computer to check tongue images quantitively in order to make tongue diagnosis objective. To check and analyze tongue image quantitively, one important step is to segment tongue body area out of face and mouth areas, i.e. tongue image segmentation. The early work was done manually, e.g. Xinglong Yu[1], Weiliang Weng[2] and Jiehua Zhu[3] all open tongue image files and remove non-tongue area manually. This kind of tongue image segmentation is of high accuracy, but it needs professionals to carry out the work and costs a lot of time and energy. Zhongxu Zhao[4] et al. introduced a kind of tongue segmentation algorithm based on mathematical morphology and HSI model. Jijun Ren[5] et al. introduced a kind of color tongue image segmentation algorithm based on grayscale color space and automatic threshold selection. Jianqiang Du[6] et al. utilized hue and intensity information and realized a kind of adaptive multi-threshold tongue image segmentation algorithm. Mingfeng Zhu[7] et al. combined color information with spatial information and utilized greedy-rules to segment tongue images.

In this article we will introduce a kind of color tongue image fast segmentation method based on improved variational level sets. The early variational level set method can only segment grayscale images. We will improve the early method to make our method adaptable to color tongue image segmentation, and we will introduce a kind of variable time step method to increase the efficiency and accuracy of segmentation.

Traditional Level Sets

Level set method[8-9] was early introduced by Oshier and Sethian to solve the problem of evolution of variations of flame shape under the equation of thermodynamics. In level set method, the curve on closed plane is implicitly denoted as equivalent curve in 3-dimensional curved surface function $\phi(x,y,t)$, and $\phi(x,y,t)$ is called level set function. The contour of the curve is denoted by zero level set $C(t)=\{(x,y)\,|\,\phi(x,y,t)=0\}$. Level set evolution equation can be written as following.

$$\frac{\partial \phi}{\partial t} + F \mid \nabla \phi \mid = 0 \,. \tag{1}$$

In traditional level set method, there might be dithering situations on level set function. Generally, we can avoid this kind of situation to occur by initialize the level set function to sign distance function before evolution. And then we need re-initialization after every evolution. The re-initialization method can be solved by the following equation.

$$\frac{\partial \phi}{\partial t} = sign(\phi_0)(1 - \mid \nabla \phi \mid) \,. \tag{2}$$

Where $sign(\phi)$ is sign function and ϕ_0 is the function which needs re-initialization. There are a lot of re-initialization methods for level set function, e.g. the methods mentioned in [8][10][11]. When one side of evolving curve is steeper than the other side, it may lead to a failure to re-initialization work. As a remedy of keeping level set function evolving stably, re-initialization work may cost highly, lead to a certain side effect, or even lead to evolution failure. Nevertheless, variational level sets can overcome the shortcomings mentioned above and avoid the re-initialization work.

Variational Level Sets

It's well known that a sign distance function must meet $|\nabla \phi| = 1$. So any function ϕ which meets $|\nabla \phi| = 1$ is the sign distance function plus a constant. We can use the following integral form to denote the similarity between function ϕ and sign distance function.

$$P(\phi) = \iint_{\Omega} \frac{1}{2} (1 - \mid \nabla \phi \mid)^2 \, dxdy \,. \tag{3}$$

Then we can define the following energy variational formula.

$$\varepsilon(\phi) = \mu P(\phi) + \varepsilon_{ext}(\phi) \,. \tag{4}$$

Where $\mu > 0$ and it is used to control the degree how function ϕ deviates from sign distance function. $\varepsilon_{ext}(\phi)$ is the outer energy used to drive zero level set to evolve, and $P(\phi)$ is inner energy.

To drive the curve to evolve towards the target boundary, we will define the formula of outer energy. Firstly, we improved the boundary feature weight function to make the method adaptable to color tongue segmentation. The new boundary feature weight function is defined as following.

$$g_c = \frac{1}{1 + \mid \nabla G_\sigma * I * H_v \mid^2} \,. \tag{5}$$

Where G_σ is Gaussian kernel function with standard deviation σ, *I* is the intensity of image after normalization, H_v is the variational hue after normalization [12].

$$H_v(x, y) = \begin{cases} ToOne(H(x,y) + 128) & H(x,y) < 128 \\ ToOne(H(x,y) - 128) & H(x,y) \geq 128 \end{cases} . \tag{6}$$

Where $H(x, y)$ is the hue of pixel at (x, y) the range of which is [0, 359], $ToOne(x)$ is the normalization function, and $ToOne(x) = (x\text{-}Min)/(Max\text{-}Min)$. Now, we define outer energy formula which drives the curve to evolve.

$$\varepsilon_{ext}(\phi) = \lambda L_g(\phi) + \nu A_g(\phi) \,. \tag{7}$$

Where $\lambda > 0$ and γ is a constant. $L_g(\phi)$ and $A_g(\phi)$ are defined as following.

$$L_g(\phi) = \iint_{\Omega} g_c \delta(\phi) \mid \nabla \phi \mid dxdy \,. \tag{8}$$

$$A_g(\phi) = \iint_{\Omega} g_c H(-\phi) dxdy \,. \tag{9}$$

Where $\delta(\phi)$ is Dirac function and *H* is Heaviside function. They are defined respectively as following.

$$H(x)=\begin{cases}1 & x\geq 0\\ 0 & x<0\end{cases}. \tag{10}$$

$$\delta(x)=\frac{dH(x)}{dx}. \tag{11}$$

From Eq. 3, Eq. 4, Eq. 7, Eq. 8 and Eq. 9, we can get partial differential function of total energy $\varepsilon(\phi)$.

$$\frac{\partial\varepsilon}{\partial\phi}=-\mu\left[\Delta\phi-div(\frac{\nabla\phi}{|\nabla\phi|})\right]-\lambda\delta(\phi)div\left(g_c\frac{\nabla\phi}{|\nabla\phi|}\right)-vg_c\delta(\phi). \tag{12}$$

Where Δ is Laplacian operator. To make Eq. 12 minimal, ϕ must meet Euler equation $\frac{\partial\varepsilon}{\partial\phi}=0$. The steepest descending process used to make total energy ε minimal can be denoted as following gradient flow.

$$\frac{\partial\phi}{\partial t}=\mu\left[\Delta\phi-div\left(\frac{\nabla\phi}{|\nabla\phi|}\right)\right]+\lambda\delta(\phi)div\left(g_c\frac{\nabla\phi}{|\nabla\phi|}\right)+vg_c\delta(\phi). \tag{13}$$

This gradient flow is the evolution equation of level sets.

Implementation of Variational Level Sets

In real algorithm, we can make smooth transformation to Dirac function $\delta(x)$, and can get the following function $\delta_\varepsilon(x)$.

$$\delta_\varepsilon(x)=\begin{cases}0 & |x|>\varepsilon\\ \frac{1}{2\varepsilon}[1+\cos(\frac{\pi x}{\varepsilon})] & |x|\leq\varepsilon\end{cases}. \tag{14}$$

Where ε is an experiential value, and in experiment $\varepsilon=1.5$. All equations' partial derivative $\frac{\partial\phi}{\partial x}$ and $\frac{\partial\phi}{\partial y}$ in section 3 can be estimated by centered difference, and partial derivative $\frac{\partial\phi}{\partial t}$ can be estimated by forward difference. Through the difference scheme, we can make an estimation to Eq. 12. This difference equation can be denoted as following iteration equation.

$$\phi_{i,j}^{k+1}=\phi_{i,j}^{k}+\tau L(\phi_{i,j}^{k}). \tag{15}$$

Where $L(\phi_{i,j}^{k})$ denotes the estimation of right side of Eq. 12 in No. *k* iteration

Time Step

If the value of time step τ is larger, the speed of curve evolution is faster and at the same time it may lead to that evolving curve crosses the target's boundary; in the contrary, if the value of time step τ is smaller, the speed of curve evolution is slower and at the same time it may lead to that evolving curve doesn't reach the target's boundary. Both cases are not expected. In article [13], the author said that time step τ and coefficient μ must meet $\tau\mu<\frac{1}{4}$, and to compromise between speed and accuracy, for most images, we can let $\tau\leq 10$. Herein, we introduce a kind of variable time step method, which can ensure both high speed and accuracy of curve evolution. In experiment, we assume the step number is *n*. Then we can get the following equation about τ.

$$\tau(n)=\tau(0)-vn. \tag{16}$$

Where, in the experiment, $\tau(0)$ is 40 and v is 0.18. As we can know from Eq. 16, τ is reducing with speed v, until it reduces to a small value. Therefore, the level set curve evolves at a high speed at first; when the curve is close to the boundary of target, it evolves at a low speed to ensure that the curve wouldn't cross the boundary.

Initialization of Level Set Function

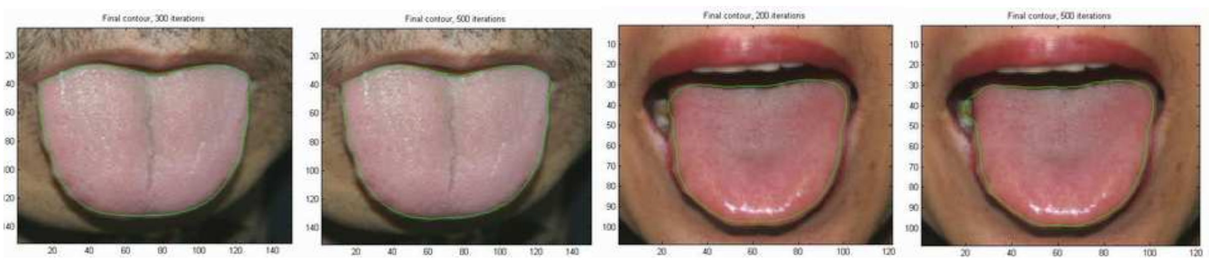
Assume Ω_0 is a subset of Ω, and Ω_1 is the set of points on the boundary of Ω_0. Then level set initialization function can be denoted as following.

$$\phi_0(x,y)=\begin{cases}-\alpha & (x,y)\in\Omega_0-\Omega_1\\ 0 & (x,y)\in\Omega_1\\ \alpha & (x,y)\in\Omega-\Omega_0\end{cases}. \tag{17}$$

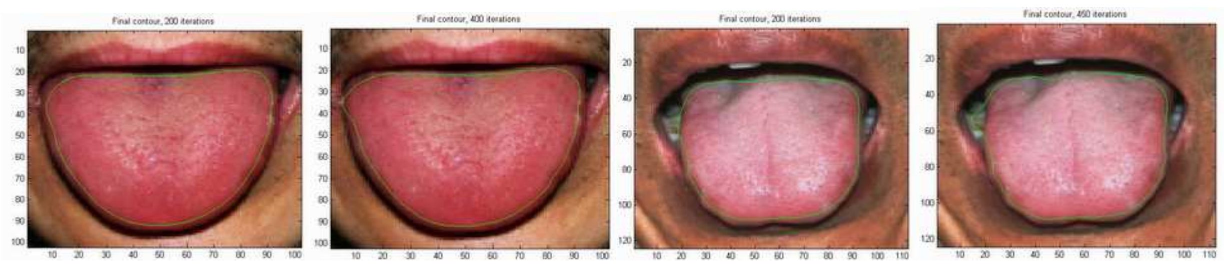
Where $\alpha>0$ and it is a constant. Because tongue area occupies a large area in whole image and the tongue area lies at the center of the image, Ω_0 should be a sub-area in central tongue area.

Comparison Experiment

4 kinds of typical tongue images (light white tongue, light red tongue, red tongue and purple tongue) are used to test both the improved method introduced in this article and the early variational level set method. The software platform is Matlab 7. The experimental results are shown in Fig. 1. In the experiment, several schemes of variable time step and several schemes of invariable time step are adopted to adapt segmentation process to different cases of tongue images.



(a) (b) (c) (d)



(e) (f) (g) (h)

Fig 1. Comparison experiment results

(a) result of light white tongue after 300 iterations using improved method; (b) result of light white tongue after 500 iterations using early method; (c) result of light red tongue after 200 iterations using improved method; (d) result of light red tongue after 500 iterations using early method; (e) result of red tongue after 200 iterations using improved method; (f) result of red tongue after 400 iterations using early method; (g) result of purple tongue after 200 iterations using improved method; (h) result of purple tongue after 450 iterations using early method

As we can know from Fig. 1, due to the adoption of variable time step, we can segment tongue image correctly, e.g. Fig. 1(a), Fig. 1(c), Fig. 1(e) and Fig. 1(g). Otherwise, for early variational level set method, due to adoption of large time step when the curve is close to the boundary of tongue, the evolving curve may cross the boundary of tongue, e.g. Fig. 1(d), Fig. 1(f) and Fig. 1(h). Additionally, the number of iterations using variable time step method is about half of the number of iterations using invariable time step method, e.g. the number of iterations using variable time step method when processing light red tongue is 200, but number of iterations using invariable time step method when processing light red tongue is 500, and the number of iterations using variable time step method when processing red tongue is 200, but the number of iterations using invariable time step method when processing red tongue is 400. The main part of this improved level set algorithm is a process of iterations, so it greatly increases the efficiency of tongue image segmentation.

Conclusion

This article, firstly, made a summary of current tongue image segmentation methods. The early variational level set method is improved, i.e. the bourdary feature weight function is improved to make this method adaptable to color tongue image segmentation, and a variable time step method is adopted to increase the accuracy and efficiency of segmentation. In comparison experiment, 4 kinds of typical tongue images are processed by the improved method and the early variational method. As the experimental results show, the efficientcy of the method introduced in this article is about 1 time higher than the early one, and its accuracy is also higher than the early one.

Acknowledgement

The method described in this article is a part of the following projects. They are the Research of Clinic Main Feature Extraction and Recognition of TCM Tongue Images supported by Natural Science Fund of Jiangxi Province(No. 2009GZS0058), the Research of TCM Tongue Aided Diagnosis System supported by Education Department of Jiangxi Province(No. GJJ10026) and TCM Tongue Aided Diagnosis System supported by TCM Scientific Research Fund of Health Department of Jiangxi Province(No. 2008A054). Here, we are very grateful for these organizations.

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