Journal of Applied Sciences

ISSN 1812-5654

Journal of Applied Sciences 13 (22): 5468-5472, 2013
ISSN 1812-5654 / DOI: 10.3923/jas.2013.5468.5472

Comparing Chan Vese Method and Canny Algorithm for Edge Detection to Tongue Diagnosis in Traditional Chinese Medicine

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Abstract: The tongue diagnosis is an important diagnostic method in Traditional Chinese Medicine (TCM). Human tongue is one of the important organs which contain the information of health status. Image segmentation has always been a fundamental problem and complex task in the field of image processing and computer vision. Its goal is to change the representation of an image into something that is more meaningful and easier to analyze. In other words, it is used to partition a given image into several parts, each of them the intensity is homogeneous. In order to achieve an automatic tongue diagnostic system, an effective segmentation method for detecting the edge of tongue is very important. We mainly compare the two steps Chan Vese Method and Canny algorithm for edge segmentation. The segmentation using Canny algorithm may produce many false edges; thus, it is not a good edge detection operator. But, for our two steps Chan Vese method can automatically select the seed regions first and then segments the tongue body successfully. Therefore, it may be useful in clinical automated tongue diagnosis system. Experiments show the results of these techniques.

Key words: Tongue diagnosis, chan vese method, canny algorithm, image edge detection

INTRODUCTION

Tongue diagnosis (Kirschbaum, 2000) is a very valuable and widely used diagnostic method in TCM, which mainly relied on the observation of tongue of patients. This method is also important in clinical applications and self-diagnosis (Pang *et al*., 2005). It is simple, nonpainful, noninvasive, immediate and inexpensive. It is like a mirror of the bowels and the pathological changes of the bowels can reflect from the change of the tongue features. So it becomes the important evidence for the diagnosis. But the current practice in TCM is mainly experience based and the quality of the visual inspection varies between medical professionals. Most experience of tongue diagnosis depends on the subjective analysis of the examiners (Maciocia, 1995), so that the diagnostic results may be uncertain. Furthermore, the skills of a small number of good experts are not easily transferable to other less experienced professionals. Thus, it is beneficial to devise more objective approaches and quantitative models to evaluate the tongue and correlate some features to patients' health conditions. To achieve the demand for automation of pathological analysis, the automatically segmenting the tongue is very important. Recently, there have been a number of attempts to develop automated digital tongue diagnostic systems using image analysis. The goal of providing an automated system for tongue analysis is not to replace conventional diagnostic methods, but to assist doctors with their decision-making by giving an early alert signal that can lead to further diagnosis by other techniques such as MRI, CT and X-Ray etc. The computerized diagnostic approach, which provides quantitative models to evaluate different features of the tongues and deduce the patients' illness, is still at an early stage of development. Many of the developed systems are only dedicated to the recognition of pathological features in tongue diagnosis and the mapping from images of the tongue to diseases is not considered. Therefore, how to make the scientific representation of a tongue, which is obtained via image processing techniques, considered here is our current work. And then, establishing a database for mapping from images of the tongue to disease immediately is our ultimate purpose in the future.

The rest of this study is organized as follows: firstly, we discuss the preparation of tongue medical image for edge segmentation. Secondly, the implementation of Canny algorithm is discussed here. Thirdly, we discuss the two steps edges detection by Chan Vese method.

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Some preprocesses are implemented and they are described here. One example of the comparison of the result of each method is shown. Finally, a conclusion is drawn.

EDGE SEGMENTATION PREPARATION

Tongue images can be captured using a specific set of image acquisition devices, including advanced camera and other corresponding lighting system. In the classification process, tongue range must be extracted from the image region. However, the tongue image includes lips, skin or teeth. Therefore, when using a variety of edge segmentation methods, most common errors are to generate during edge segmentation. The main reason is the similarity of color between tongue and skin. The coupled light source is not stable; hence, making segmentation becomes more difficult. Here, we compare two methods to explain the above reasons.

Image edge detection has many applications (Zhang *et al*., 2012; Yu *et al*., 2012; Zhao and Dan, 2012; Xu *et al*., 2012; Jiang, 2011; Liu *et al*., 2011). Edges in a digital image provide important information about the objects contained within the image since they constitute the boundaries between the objects in the image. It is a frequently performed operation in image processing applications because it is usually the first operation that is performed before other image processing tasks such as image segmentation, boundary detection, object recognition, classification, image registration and so on.

Image segmentation is an important process in most medical image analysis tasks. An image segmentation algorithm decomposes an image into regions having visual similarity and strong statistical correlation. Extraction and classification of tongue is an important process that has many applications in medical imaging. A good segmentation algorithm will benefit clinicians and patients as they provide important information for surgical planning and early disease detection.

The proposed algorithm aims to segment the given image with visually distinct colors, so a human perception based color model is preferred. The representation of color images by Red-Green-Blue color model is the conventional method. But the three components of RGB color model are highly correlated, so that the chromatic information is not suitable for using directly. Therefore, the CIELAB color space is adopted because it is convenient to convert from RGB and also intimately related to human perception. If we need a perceptual uniform to do the tongue images comparison, we need to choose a suitable color space first. Perceptually uniform means that a change of the same amount in a color value should produce a change of about the same visual importance. When storing colors in limited precision values, this can improve the reproduction of tones. Lab values do not define absolute colors unless the white point is also specified. Often, in practice, the white point is assumed to follow a standard and is not explicitly stated (e.g., for "absolute colorimetric" rendering intent ICC L*a*b* values are relative to CIE standard illuminant D50, while they are relative to the unprinted substrate for other rendering intents). One of the most important attributes of the L*a*b*-model is device independence. This means that the colors are defined independent of their nature of creation or the device they are displayed on.

After finishing the color space transformation mentioned above, we get color descriptions that are natural and intuitive to humans. Then, the input image is smoothened by using morphological operators to get recovered from noise particles.

EDGE DETECTION BY CANNY ALGORITHM

In 1986, Canny edge detection operator was proposed on optimization algorithms for edge detection. Relatively simple algorithm to make the whole process effectively is executed and has been widely used but Canny operator has the defect that being vulnerable to various noise disturbances. Thus, there are certain limitations of its concrete application (Wang and Fan, 2009).

The detecting process of the Canny algorithm consists of the following steps (Pan and Wang, 2008):

Step 1: Use the Gaussian filter smoothing image to restrain noise

Step 2: Calculating the gradient magnitude M (x,y) and the gradient direction H (x,y) of the image M (x,y) is defined as follows:

$$M(x, y)=\sqrt{E_x(x, y)^2+E_y(x, y)^2} \tag{1}$$

The H(x,y) is defined as follow:

$$H(x, y)=\arctan\left(E_x(x, y)/E_y(x, y)\right) \tag{2}$$

Ex and Ey are the result what the image being affected by the filter along the row-column direction:

Step 3: Do non-maximum suppression for the gradient magnitude

Step 4: Dual-Threshold algorithm is adopted to detect and connect edges

The main defects of the traditional Canny algorithm are the usage of Gaussian filter. When smooth the noise, some edge is also smoothed. Besides, the detection results have some isolated edges and some false edges.

TWO STEPS EDGE DETECTION BY CHAN VESE METHOD

The main idea in this section is to detect regions (objects) and their boundaries and to isolate and extract individual components from a tongue medical image. This can be done by using K-means method firstly to detect regions used as seed region's boundary for the Chan Vese method's initial guess. Therefore, Chan Vese method will stop on the desired boundary successfully. The final image segmentation results are one closed boundary per actual region.

Preprocessing steps for chan vese algorithm: As in this heading, they should be Times New Roman 11-point boldface, initially capitalized, flush left, with one blank line before and one after.

Firstly, for skin like color image segmentation, it performs better in CIELAB color space than RGB color space. Therefore, Image is first converted to CIELAB color space. This transform is based on ITU-R Recommendation BT.709 using the D65 white point reference. The error in color space transformation is approximately 10-5. RGB values can be either between 0 and 1 or between 0 and 255. Three dimensional color histogram from CIELAB are generated. Secondly, in order to find the most suitable cluster numbers, we use the histogram to search for local maximum peaks. After this process, we find the label image where each pixel is the cluster label it belongs to. Finally, the edges of the label image are used for the seed regions for Chan Vese method automatically. In so doing, it provides to automate Chan Vese edge segmentation for a batch work when large patient tongue images are needed for diagnosis.

However, giving a suitable initial K-means seed still needs the experience of the physicians. Here, we simply discuss different initial K-means seed will yield different result. For the first case, five initial seeds are given. After searching the peaks from color histogram, only two seeds are used for K-means seeds. As shown in Fig. 1a, only two labels appear in the result image. For the second case, ten seeds are given, only five seeds are chose for K-means seeds. As shown in Fig. 1b, only five labels appear in the result image. For the third case, fifteen seeds are given, only thirteen seeds are chose for K-means seeds. As shown in Fig. 1c, only thirteen labels appear in the result image.

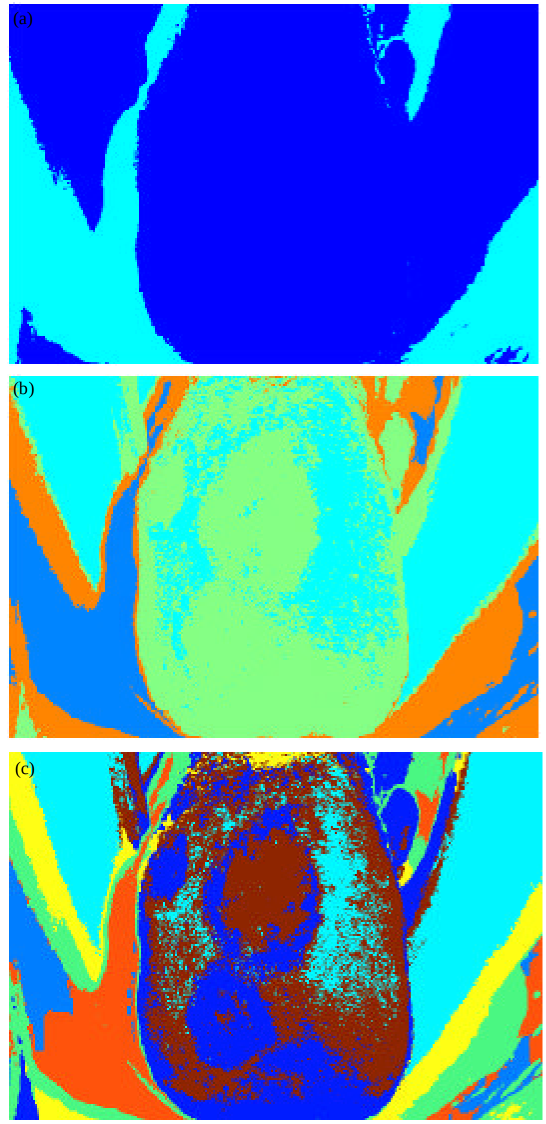

Fig. 1(a-c): Two labels image got from five initial seeds are given, (b) Five labels image got from ten initial seeds are given and (c) thirteen labels image got from fifteen seeds are given

In this stage of implementation, we find to give a proper initial seeds to yield right labels used for the Chan Vese's initial seed regions is still a challenging task for color image segmentation automation. We hope to solve this problem in the future.

Chan vese method: Active contour model, or snakes, proposed by Kass *et al*., 1988. has been proved to be an efficient framework for image segmentation. Since the active contour model was proposed, many methods have been proposed to improve it, in which level set method proposed by Osher and Sethian, 1988. is the most important and successful one. Recently, region-based level set methods (Tsai *et al*., 2001a, b; Gao and Bui, 2005) have been proposed and applied to image segmentation filed by incorporating region-based information into the energy functional. Unlike edge-based level set methods using image gradient, region-based methods usually utilize the global region information to stabilize their responses to local variations (such as weak boundaries and noise). Thus, they can obtain a better performance of segmentation than edge-based level set methods, especially for images with weak object boundaries and noise. Among the region-based methods, Chan-Vese model is one of the most popular.

Based on the Mumford and Shah (1989). for segmentation, Chan and Vese, 2001. proposed an easily handled model, or called Chan-Vese (CV) model, to detect objects whose boundaries are not necessarily detected by the gradient. Mumford-Shah model was firstly proposed as a general image segmentation model by Mumford and Shah. Using this model, the image is decomposed into some regions. Inside each region, the original image is approximated by a smooth function. The optimal partition of the image can be found by minimizing the Mumford-Shah functional. Chan and Vese successfully solved the minimization problem by using level set functions, which utilized the global image statistics inside and outside the evolving curve rather than the gradients on the boundaries.

The Chan Vese (CV) model is an alternative solution to the Mumford-Shah problem which solves the minimization of Mumford-Shah energy functional by minimizing the following energy functional:

$$E_{CV}(c_1, c_2, C) = \mu.\text{Length}(C) + ?_1 . \int_{\text{incide}(C)} |\mu 0(x, y) - c_1|^2 \, dx\, dy + ?_2 . \int_{\text{outside}(C)} |\mu_0(x, y) - c_2|^2 \, dx\, dy \quad (3)$$

where μ, λ_1 and λ_1 are positive constants, usually fixing $\lambda_1 = \lambda_2 = 1$. c1 and c2 are the intensity averages of μ_0 inside C and outside C, respectively. To solve this minimization problem, level set method is used which replaces the unknown curve C by the level set function ϕ (x, y), considering that ϕ (x, y)> 0 if the point (x,y) is inside C, ϕ (x, y) < 0 if (x,y) is outside (x,y) and ϕ (x, y) = 0, if (x,y) is on C. Thus, the energy functional E^{CV} (c_1, c_2, C) can be reformulated in terms of the level set function ϕ (x, y) as follow:

$$E_{CV}(c_1, c_2, f) = \mu.\int_O d_e(f(x, y))|\nabla f(x, y)|dx\,dy + ?_1 . \int_O |\mu_0(x, y) - c_1|^2 H_e(f(x, y))|dx\,dy + ?_2 . \int_O |\mu_0(x, y) - c_2|^2 (1 - H_e(f(x, y)))|dx\,dy \quad (4)$$

Fig. 2: Original input image

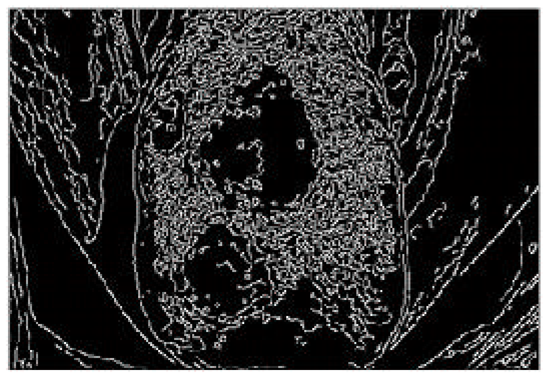

Fig. 3: Edge segmentation by Canny method

where, H_ε (z) and δ_ε are, the regularized approximation of Heaviside function H (z) and Dirac delta function δ (z) as follows:

$$H(z) = \begin{cases} 1 & \text{if } z \geq 0, \\ 0 & \text{if } z < 0, \end{cases} \quad d(z) = \frac{d}{dz} H(z) \quad (5)$$

This minimization problem is solved by taking the Euler-Lagrange equations and updating the level set function by the gradient method.

COMPARISON OF THESE TWO METHODS TO TONGUE DIAGNOSIS

In Fig. 2, it is the original input tongue image. The result in Fig. 3, using Canny algorithm can produce more noise and more false edges. Canny edge detector can extract boundaries but due to abrupt change in brightness levels of image, correct and smooth edges are not obtained. More accurate one would be obtained if morphological operator is applied to remove small voids and short lines. But it is still not easy to select one closed

Fig. 4: Edge segmentation by two steps Chan Vese method

edge of the tongue body, so it is not suitable for use in the tongue image. The result of two steps Chan Vese method is shown in Fig. 4. It can be achieved automatically select the best edge information.

CONCLUSION

In this study, Canny algorithm and two steps Chan Vese method for image edge detection approach have been successfully applied. By Canny algorithm, some false edges occur. While using two steps Chan Vese approach for image edge detection, we can effectively segment the tongue without affecting the integrity of the further tongue diagnosis. Experimental results show that the implemented intuitionistic edge detector exhibits much better performance than the competing operators and may efficiently be used for the detection of edges in digital images.

This is the first step to establish a automated tongue diagnosis system and will improve the scientific representation of tongue diagnosis in Traditional Chinese Medicine. In the future, we hope to continue to use this effective method for the separation between tongue and tongue coating, which is useful in the realization of physiological and pathological status within human body from the viewpoint of Traditional Chinese Medicine. Furthermore, more efficient codes can be exploited to further reduce the computational load of the proposed algorithm for future research work.

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