Journal of Applied Sciences

ISSN 1812-5654

Journal of Applied Sciences 13 (18): 3676-3683, 2013
ISSN 1812-5654 / DOI: 10.3923/jas.2013.3676.3683

Automatic Color Segmentation by Colormap and Edge Detection by Chan Vese Method for Tongue Image

[1]Yen-Sheng Chen, [2]Ming-Chih Huang and [3]Shao-Hsien Chen
[1]Department of Creative Product and Technological Application, Lan Yang Institute of Technology, China
[2]Department of Industrial Design, National Taipei University of Technology, China
[3]Department of Mechanical Engineering, National Chin-Yi University of Technology, China

Abstract: The tongue diagnosis is an important diagnostic method in Traditional Chinese Medicine (TCM). Human tongue is one of the important organs which contains 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 another one with more meaningful which is 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 is necessary for detecting the edge of tongue. We mainly address by using different colormap for color segmentation and Two-Step-Chan Vese Method for edge detection. The use of colormap for color segmentation will help the initial guess of boundary contour to detect the edges of tongue body by Chan Vese Method. Therefore, it may be useful for developing a clinical automated tongue diagnosis system. The results of experiments implement the proposed methods.

Key words: Tongue diagnosis, chan vese method, colormap, 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.

In this study, we use the palettes for the screen of classic games such as Nintendo Gameboy, Sega Master System, Super Nintendo Entertainment System and TurboGrafx-16. We will discuss the results of color segmentation for tongue image and discuss the methods

Corresponding Author: Yen-Sheng Chen, Department of Creative Product and Technological Application, Lan Yang Institute of Technology, China

we treat certain conditions of images using the features we provided for image processing. Finally, we will discuss the benefits or flaws of each feature to specific palettes, or types of images.

The rest of this study is organized as follows: Firstly, we discuss the preparation of tongue medical image for edge detection. Secondly, the implementation of colormap for color image segmentation is discussed here. Thirdly, we use the segmentation discussed in previous section to find the contour as the initial guessed boundary curve for edges detection by Chan Vese Method. 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 DETECTION 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 detection methods, most common errors are to generate during edge detection. 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, 2010; 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.

COLOR IMAGE SEGMENTATION

The use of an adequate correct color transfer function (colormap) becomes keys to the detection of visual details and making them perceivable to the typical discerning end user. However, the user is still thrust with the burden of knowing what color scheme to use and what frequency to place the desired colors in. Thus the time it takes to create a meaningful colormap which proves useful is significantly increased by adding these proven perception constraints. Prepackaged colormaps might fail in offering the user the flexibility to create unique results and the only other option of creating aesthetically coherent colormaps from scratch requires know-how and time unavailable to most researchers. Therefore, using some typical theme of colormap or palette will present some aesthetical result for visual representation. It is easier than mathematically aid in the color selection, such that the resulting colors prove distinguishable to human perception (Healey, 1996).

In this study, we use games on the Nintendo Entertainment System to see the result of color segmentation. We will perform the task of taking RGB images and transforming these images based on color palettes of a variety of older game consoles. The consoles we have given attention to are (primarily) Nintendo Entertainment System (NES), Nintendo Gameboy (GB), Sega Master System (SMS), Super Nintendo Entertainment System (SNES) and TurboGrafx-16 (TG16). We will also address the issues with directly mapping to any one of these palettes and how the MATLAB code (Page, 2012) provides enhancements to resolve these issues for many cases.

Palettes: Here, five different classic game console color palettes are used. Our goal is not to mimic the limitations of screen drawing for each system but to effectively map to their color systems. Since our main focus is the NES color palette, we have supplied transformations best suited to that particular aesthetic look. In each palette described, we give their specifications and what we took into consideration for each palette.

NINTENDO ENTERTAINMENT SYSTEM (NES)

The NES has a YPbPr sixty four-color palette where only fifty four to fifty six of the colors are useful. The remainders of the colors are all black. For the effectiveness of our program, we have removed all the redundant colors from our color map and kept only fifty five from the original palette.

Nintendo gameboy (GB): Unlike the NES palette, the Nintendo Gameboy has only two-bit monochrome grayscale support. As a consequence, there are only four intensities supported. In our software, we emulated the green-like appearance of the screen of the Nintendo Gameboy.

Sega master system (SMS): Consisting of sixty four colors, the Sega Master System color palette is a six-bit RGB system where each color component is encoded by two bits. Each bit change spreads intensity values between 0 and 255 in a roughly uniform manner for each color component.

Super nintendo system (SNES): The SNES color palette is a fifteen bit RGB color palette. Each color component consists of five bits of encoding. RGB values are distributed uniformly for each band as each bit change. In our palette we are not considering the special modes of the SNES graphics chip. This palette has exactly 32,768 colors.

TurboGrafx-16 (TG16): Finally, the TurboGrafx-16 color palette consists of 512 colors. This palette is a nine-bit RGB system where each color channel is encoded using three bits. As with the SNES, RGB values are uniformly spread.

Image transforms: In this subsection, we will describe each of our methods of enhancement to assist achieving a good quality image. All transformations occur before mapping to any particular color palette. These general transforms are meant to assist the mapping process to enhance the entire image depending on the palette.

Intensity adjustment: It adjusts the intensity levels of a grayscale image. In our implementation we apply this function to each color band. This is meant to aid images with poorly lit conditions.

Histogram equalization: The transform applies histogram equalization in the RGB-space to each color band. In experiments we found that this filtering aids the mapping of images with overall poor contrast.

Discrete cosine transform (DCT): Once DCT is applied to each color band, the transform employs a low-pass filter. The threshold is tunable in our implementation. This kind of transformation is for stylistic impression. Some retro artists make use of multiple kinds of colors to emphasize shades where normally only a shorter range may only provide little shading. This transform may result for higher range color palettes in rainbow effects. For palettes like the GB palette, this can serve useful for lighting effects. We wish to simulate this effect. If the filter parameter is low, there will be less structure and a high parameter value will give a high contrast image.

Observations: As shown in Fig. 1 is our test tongue color image. Only three of the color palettes are demonstrated in our observations. Without including TurboGrafx-16 and Super Nintendo Entertainment System in our results, these two color palettes are high enough quality. We analyzed the NES, GB and SMS color palette results. Let us give our observations.

Nintendo entertainment system (NES): As seen in Fig. 2, we were successful at creating images which appear to capture the colors of the NES. Fig. 2a shows NES with full image DCT processing, Fig. 2 (b) represents NES with histogram equalization processing and Fig. 2c means the tongue image with intensity adjustment processing.

With darker images, it is very common to obtain very dark yellow tones. This is due to the next darkest tone in the palette from dark gray being this tone of yellow. This can be very unappealing unless properly treated. The NES palette is less distributed than other palettes due to the large number of duplicate colors. Since colors in terms of the RGB space are not uniform, experimentation is quite common to gather satisfactory results.

Figure 3 shows the tongue image without any transformations mapped to the NES palette. We see somedark yellow but a lot of the common colors do not reflect boundaries very well. We found experimentally that intensity adjustment to increase the contrast and using $\gamma = 1{:}2$ to segment the image by making the image darker improved the quality along with emphasizing the edges to result in Fig. 2c.

Present study show that brighter images with high contrast, or images with darker colors but low contrast are improved through image intensity adjustment. If an image

Fig. 1: Test image

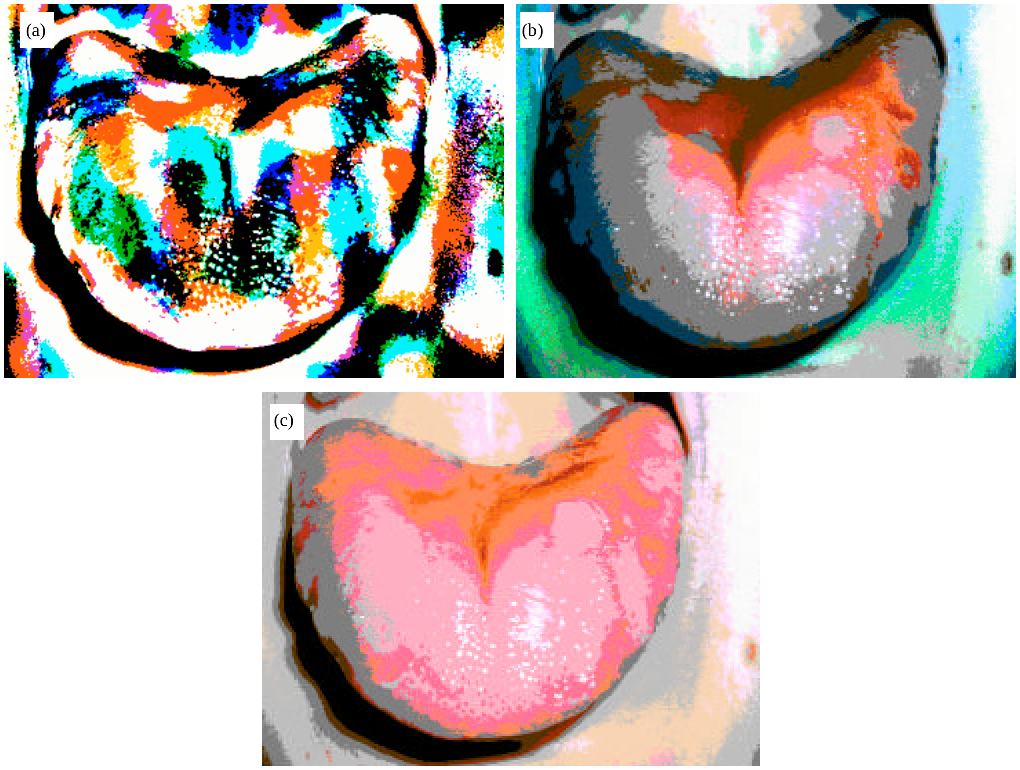

Fig. 2(a-c): Image produced from test images with NES palette, (a) Enhanced by DCT, (b) Enhanced by HE and (c) Enhanced by intensity adjustment

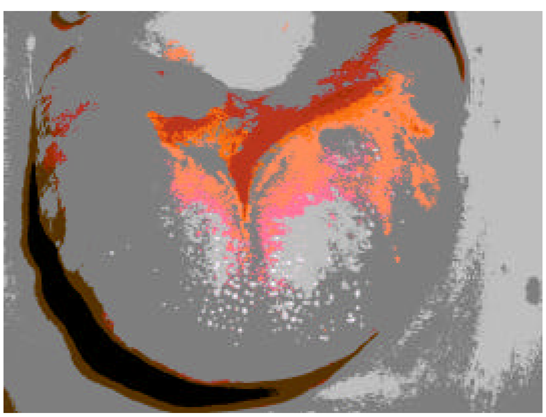

Fig. 3: Image processed with only mapping to NES palette

is applied to intensity adjustment, normally increasing gamma will help improve the results. On the other hand, images with lots of brightness and low contrast we found are resolved through histogram equalization. We predict this is due to the poor segmentation which can be improved by spreading levels across all color bands as it may include lots of gray originally. If no transformations are used, an image with actual NES colors will remain unchanged after processing as shown in Fig. 3.

Nintendo gameboy (GB): We found results with the GB palette to be exceptional. Since the GB palette is only four intensities, it is a matter of obtaining the detail wanted through either segmenting brighter, or darker portions of the image. Figure 4a shows GB with full image DCT processing, Fig. 4b represents GB with histogram equalization processing and Fig. 4c means the tongue image with intensity adjustment processing.

For DCT transformation, it serves especially useful with this palette. For darker images treating, full image DCT allows for further textures to be shown by representing many different shades with different RGB values. When these various RGB values are mapped to the GB palette these strange colors become better texture and lighting for the image which can capture the style of GB graphics very well.

An alternative to treating high contrast or bright images is to use intensity adjustment, with varying gamma adjustment. By varying the contrast levels across all color

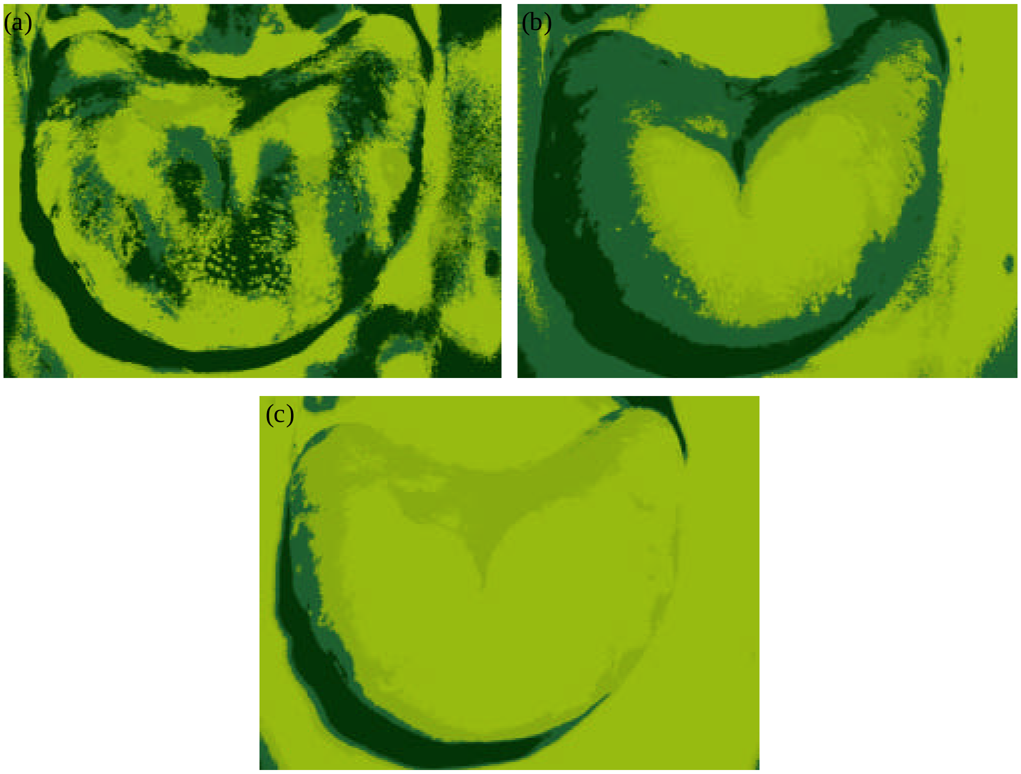

Fig. 4 (a-c): Images produced from test images with GB palette, (a) Enhanced by DCT, (b) Enhanced by HE and (c) Enhanced by intensity adjustment

Fig. 5: Image processed with only mapping to GB palette

bands, the function will transform the image to level out the intensities. Once these are leveled, darkening the image is often the solution for more detail. Also, we predict images with little contrast, or lots of similar colors are resolved with histogram equalization. We believe this is due to lack of variation of intensities across the bands along with value in each band. Histogram equalization will equalize the levels across each band to for better segmentation in the GB palette mapping phase. If no transformations are used, an image with actual GB colors will remain unchanged after processing as shown in Fig. 5.

Sega master system (SMS): From our results (Fig. 6), it is evident one flaw comes apparent due to the palette. There is a dilution of very bright blue due to the lack of near-white values in this palette. Close to white values are mapped immediately to the light blue but in ways this is similar in style to some SMS style graphics but may not be desirable for all cases. An interesting effect observed due to its close relationship with the NES palette (both being very close in number of colors) is its effect on digital images.

Figure 6a shows SMS with full image DCT processing, Fig. 6b represents SMS with histogram equalization processing and Fig. 6c means the tongue image with intensity adjustment processing. Figure 7 is effectively mapped but actually causes less detail to appear but looked just like if it were on the sega master

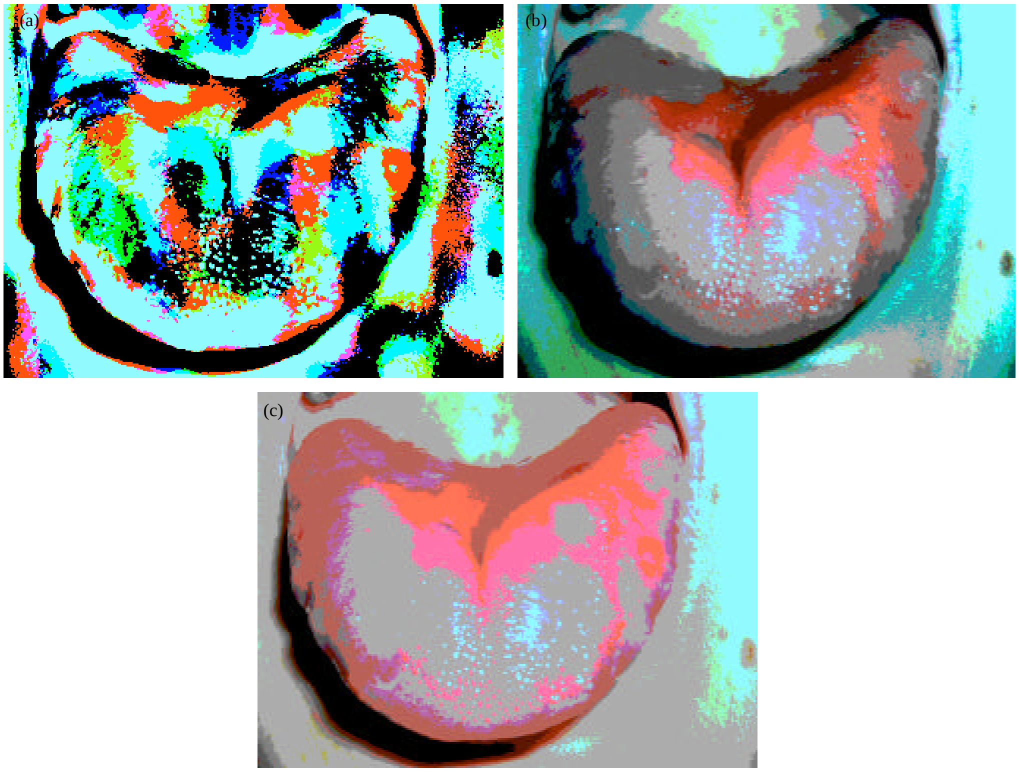

Fig. 6 (a-c): Images produced from test images with SMS palette, (a) Enhanced by DCT, (b) Enhanced by HE and (c) Enhanced by intensity adjustment

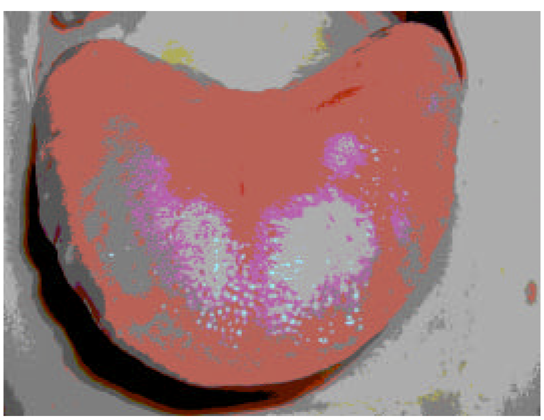

Fig. 7: Image processed with only mapping to SMS palette

System. This is due to the closely related colors being mapped to the same colors while the varying outlines remain the same. This is a desirable effect and only requires mapping to achieve. To capture SMS like graphics, it has a reverse relationship to the NES processing. We achieve an SMS appearance on photographs when applied to histogram equalization. Since the SMS palette is a very distributed variation of our RGB color system with less colors, spreading out the levels on each band will map much more effectively than if we only considered the contrast. If no transformations are used, an image with actual SMS colors will remain unchanged after processing as shown in Fig. 7.

DISCUSSION

Using a variety of techniques such as histogram equalization, intensity adjustment, discrete cosine transform, bilateral filtering, edge detection, down-sampling, indexed images and gamma adjustment we presented an effective method for users to create classic images for tongue color image. We believe such processing result would be useful for color segmentation which would be the initial guess of contour used for edge detection by Chan Vese Method.

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 colormap segmentation as mentioned in previous section. In so doing, Chan Vese Method will stop on the desired boundary automatically and successfully. The final image segmentation results are one closed boundary per actual region.

Preprocessing steps for chan vese method: 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. Secondly, based on bilateral filtering, we implement smoothing procedure. Using W = 1 and sigma = 1 supplies a smoothing operator without losing edge content for images. This transformation yields a stylistic effect which can emulate the effects classic game images have for shading in some cases. Finally, for hard to treat images, gamma adjustment can help map images with poor segmentation, or poor lighting. It is also tunable in our implementation. By default, the positive floating point value $\gamma = 1$. If gamma is equal to one, then there will be no change in effect. If $\gamma > 1$, then darker portions of the image such as shadows will become darker. If $\gamma < 1$ darker portions of the image will become brighter.

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. Based on the Mumford-Shah functional (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:

$$E^{CV}(c_1, c_2, C) = \mu.\text{Length}(C) + \lambda_1.\int_{\text{inside}(C)} |u_0(x,y) - c_1|^2\,dxdy + \lambda_2.\int_{\text{inside}(C)} |u_0(x,y) - c_2|^2\,dxdy \quad (1)$$

where, μ, λ_1 and λ_2 are positive constants, usually fixing $\lambda_1 = \lambda_2 = 1$. c_1 and c_2 are the intensity averages of μ_2 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 $\phi(x, y)$, considering that $\phi(x, y)>0$ if the point (x, y) is inside C, $\phi(x, y)<0$ if (x, y) is outside (x, y) and $\phi(x, y) = 0$, 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 $\phi(x, y)$ as follow:

$$\begin{aligned} E^{CV}(c_1, c_2, \phi) = {} & \mu \bullet \int_\Omega [\![\delta_\varepsilon(\phi(x,y)) |\nabla\phi(x,y))| dxdy]\!] \\ & + \lambda_1 \bullet \int_\Omega |u_0(x,y) - c_1|^2 H_\epsilon(\phi(x,y))| dxdy \quad (2) \\ & + \lambda_2 \bullet \int_\Omega |u_0(x,y) - c_2|^2 H_\epsilon((\phi(x,y)))| dxdy \end{aligned}$$

where, $H_\varepsilon(z)$ and $\delta_s c$ are, the regularized approximation of Heaviside function H(z) and Dirac delta function $\delta(z)$ as follows:

$$H(z) = 1 \text{ if } z | 0,\ H(z) = 0 \text{ if } z < 0,\ \delta(z) = \frac{d}{dz} H(z) \quad (3)$$

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

Fig. 8: Edge detection by two-step-chan vese method

Result of chan vese method to edge detection in tongue diagnosis: The result of Two-Step-Chan Vese Method is shown in Fig. 8. It can be achieved automatically select the best edge information.

CONCLUSION

In this study, we successfully use palettes of some classic game console for color segmentation in the first part and apply Two-Step-Chan Vese Method for image edge detection in the second part. Through the proposed method, the Two-Steps Chan Vese Method for image edge detection, we can effectively segment the image of the tongue without affecting the integrity of information for the further tongue diagnosis. The experimental results show that the proposed method, may efficiently be used for the detection of edges in digital images and exhibits much better performance than the competing operators.

This is the preliminary stage to establish an automated tongue diagnosis system and will improve the scientific representation of tongue diagnosis in Traditional Chinese Medicine. In the future, basing on this effective method, an advanced technology will be developed to separate tongue and tongue coating in a digital image 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.

REFERENCES

Chan, T.F. and L.A. Vese, 2001. Active contours without edges. IEEE Trans. Image Process., 10: 266-277.

Healey, C.G., 1996. Choosing effective colours for data visualization. Proceedings of the IEEE Visualization, October 27-November 1, 1996, San Francisco, CA., USA., pp: 263-270.

Jiang, Q.L., 2010. Edge detection for color image based on CNN. Adv. Inform. Sci. Serv. Sci., 3: 61-69.

Kass, M., A. Witkin and D. Terzopoulos, 1988. Snakes: Active contour models. Int. J. Comput. Vision, 1: 321-331.

Kirschbaum, B., 2000. Atlas of Chinese Tongue Diagnosis. Eastland Press, Seattle, USA., Pages: 260.

Liu, J., C. Shi and M. Gao, 2011. Edge detection based on statistical threshold stockwell transform. Int. J. Digital Content Technol. Appl., 5: 189-197.

Maciocia, G., 1995. Tongue Diagnosis in Chinese Medicine. Eastland Press, Seattle, USA., Pages: 210.

Mumford, D. and J. Shah, 1989. Optimal approximations by piecewise smooth functions and associated variational problems. Commun. Pure Applied Math., 42: 577-685.

Osher, S. and J.A. Sethian, 1988. Fronts propagating with curvature-dependent speed: Algorithms based on Hamilton-Jacobi formulations. J. Comput. Phys., 79: 12-49.

Page, D., 2012. Retrogressive classic game image processing. The MathWorks, Inc.

Pang, B., D. Zhang and K. Wang, 2005. The bi-elliptical deformable contour and its application to automated tongue segmentation in Chinese medicine. IEEE Trans. Med. Imaging, 24: 946-956.

Xu, G., M. Zhou, Z. Xiong and Y. Yin, 2012. An improved adaptive fusion edge detection algorithm for road images. Adv. Inform. Sci. Serv. Sci., 4: 129-137.

Yu, J., J. An, Y. Wang, Z. Liu and J. Liu, 2012. A new region-based active contour edge detection algorithm for oil spills remote sensing image. J. Converg. Inf. Technol., 7: 112-119.

Zhang, J., J. Zhou, K. He and H. Li, 2012. Image edge detection using quantum ant colony optimization. Int. J. Digital Content Technol. Appl., 6: 187-195.

Zhao, Y.Q. and S. Dan, 2012. Study on the defect detection technology based on wavelet analysis and image edge detection. Int. J. Digital Content Technol. Appl., 6: 125-132.