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A Novel Imaging System for Tongue Inspection

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Abstract

A digital imaging and modeling system is developed for tongue inspection that has been an important diagnostic method of Traditional Chinese Medicine (TCM). The system includes image acquisition, color calibration, image segmentation, feature extraction and classification functions. The preliminary results show that the color and texture features are sensitive to the abnormal tongues.

Introduction

For over two thousand years, visual inspection of the tongue has been a unique and important diagnostic method of Traditional Chinese Medicine (TCM). Observing the abnormal changes in the tongue proper and the tongue coating can aid in diagnosing diseases. Clinic data have shown significant connections between various viscera cancers and abnormalities in the tongue and the tongue coating [Yao, 1996]. Since the early 1980s medical professionals in China have systematically studied the relationship between various cancers and tongue signatures. Their results have been published in national medical journals [Li, et al, 1987]. For instance, China TCM Society, China Cancer Society and TCM Diagnosis Association conducted a national project that included cases of 12,448 cancerous patients, 1,628 non-cancerous patients and 5,578 normal patients [TCMA, 1987]. The results statistically showed that there are significant changes of color, coating, shape and dorsum shape of the tongues of cancerous patients versus those tongues of non-cancerous patients or normal subjects.

Visual inspection of the tongue offers many advantages: it is a non-invasive diagnosis method, is simple and inexpensive. However, the current practice in TCM is mainly experience based or subjective. The quality of the visual inspection varies between individuals. And although there are a few experts successfully diagnosing cancers based on inspection of the tongue, their skills are not easily transferable to other medical professionals. Their expertise is limited at qualitative descriptions, not to quantitative or mathematical formulations. To circumvent this problem, We have been developing a prototype of the imaging system for the tongue inspection.

Process

We use a digital imaging system to make a picture of a patient's tongue, then use software to extract the features from the image, and finally make a diagnosis based on quantitative models. Our goal is not to replace the conventional diagnostic methods but to give an early alert signal that can lead to further diagnosis by other methods, such as MRI, CT, X-ray, colonoscopy, etc. The novel approach has various significant advantages. First, it makes the inspection objective and repeatable so that it prevents human bias and errors. Second, it can be implemented on an inexpensive personal computer or laptop computer for clinic or family use.

The imaging system consists of image acquisition, image processing, feature representation, and diagnostic models.

1. Image acquisition. Our first approach is to use a modified handheld color scanner with a microscopy slide on top of the tongue. As the scanner is gently moved from the root of the tongue to the tip, a crispy color image can be obtained. Figure 1 shows a sample image. The advantage of the method is simple so that it can avoid major color calibration and the removal of artifacts. However, it is a contacting measurement that we would try to avoid in clinic environment, and the hardware needs to be specially designed to fit the size of tongues. Our second approach is to take picture of the tongue with a commercial digital camera (640 x 480) plus a Munsell ColorChecker [McCamy, 1976] embedded inside the image. Since we have already know the color value of the test cells on ColorChecker, we can calibrate the color of the image computationally. Figure 2 shows a sample image of the second approach.

2. Image processing. We have developed a semi-automatic color calibration tool [Amots, 1994]. By manually clicking the four corners of the ColorChecker, the software can perform the transformation and find the points in each square. Then we use a linear color calibration model to recover the original color of the tongue under various lighting conditions. The tongue area is cropped by using an active contour model, "Snake" [Akgul, 1999]. It is a general algorithm for matching a deformable model to an image by means of energy minimization.

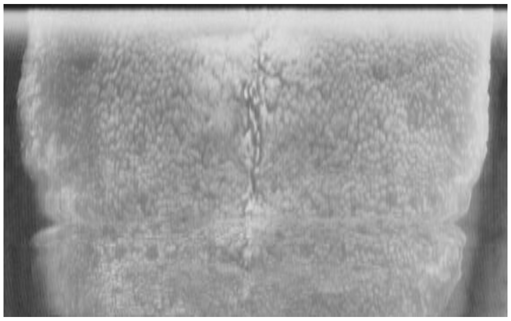

Figure 1 Image from the Handheld Scanner

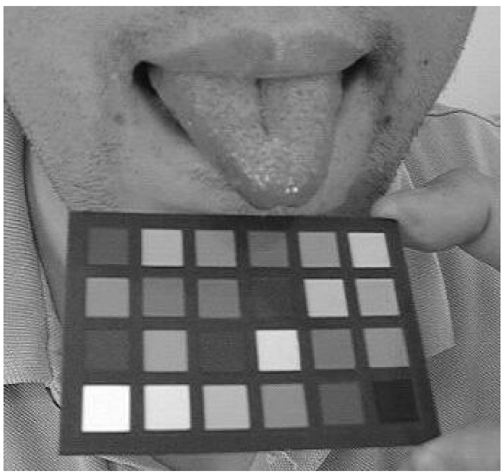

Figure 2 Imaging with Munsell ColorChecker

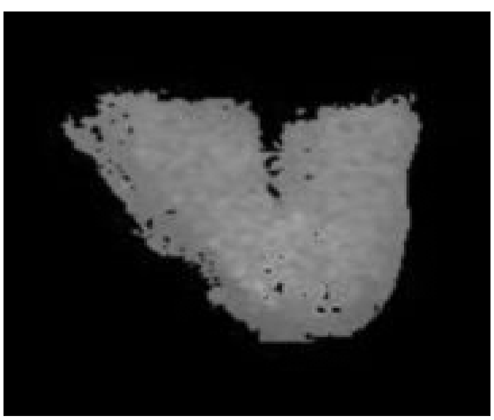

Figure 3 Cropped Image

The energy function is a weighted combination of internal and external forces. The snake is defined parametrically as $\mathbf{v}(s) = [x(s), y(s)]$, where x(s),y(s) are x, y co-ordinates along minimized can be written as the contour and $s \in [0,1]$. The energy functional to be

$$E_{\text{snake}} = \int_0^1 E_{\text{snake}}(\mathbf{v}(s))\, ds$$

$$= \int_0^1 \{[E_{int}(\mathbf{v}(s)] + [E_{image}(\mathbf{v}(s)] + [E_{con}(\mathbf{v}(s)]\}\, ds$$

where E_{int} represents the internal energy of the spline due to bending, E_{image} denotes image forces, and E_{con} external constraint forces. Usually, $\mathbf{v}(s)$ is approximated as a spline to ensure desirable properties of continuity.

Figure 2 shows an example of the cropped tongue area. To remove the highlights and shadows on the tongue, we have developed a heuristic algorithm. We convert the image from the color space of RGB to HVS and use the deviation of the Value as the cutoff criterion. Figure 3 shows an example of the image after the highlights and shadows are removed.

3. Feature representation. We convert the image from the color space of RGB to L*a*b so that we can represent the color feature with only two parameters, *a and *b. [Amots, 94] To represent the texture feature, we use Entropy and Energy Functions [Reed, 1993].

$$H_{entropy} = - \sum_i \sum_j M[i,j] \log(M[i,j])$$

$$H_{energy} = - \sum_i \sum_j M[i,j] / (1 + |i - j|)$$

where, M is a grey level co-occurrence matrix (GLCM) that contains information about the position of pixels having similar grey level values. The idea is to scan the image and keep track of how often pixels that differ by Δz in value are separated by a fixed distance d in position.

4. Classification. We use K-mean and 3-D visualization to classify the data. See Figure 4 for the illustration.

Results

1. Color Calibration. Our results shows that the color calibration method can reduce the errors between the truth value (m) and predicated value (p). The error can be estimated as following:

$$|\Delta R| = |Rm - Rp|,\ |\Delta G| = |Gm - Gp|,\ |\Delta B| = |Bm - Bp|$$

$$Error1 = \sqrt{|Rm - Rp|^2 + |Rm - Rp|^2 + |Rm - Rp|^2}$$

$$Error2 = \frac{\sqrt{|Rm - Rp|^2 + |Rm - Rp|^2 + |Rm - Rp|^2}}{\sqrt{|Rm|^2 + |Rm|^2 + |Rm|^2}}$$

Table 1. Error estimation of the color calibration method

function	Before Calibrated					After Calibrated				
	|ΔR|	|ΔG|	|ΔB|	Error1	Error2 $[10^{-2}]$	|ΔR|	|ΔG|	|ΔB|	Error1	Error2 $[10^{-2}]$
Mean	25.42	26.67	39.67	57.17	26.71	14.25	5.88	10.08	20.47	8.40
Max	62.00	84.00	190.00	94.44	71.81	70.00	17.00	28.00	71.20	30.93
min	2.00	1.00	6.00	23.69	7.92	1.00	0.00	1.00	8.77	3.15
std	18.86	14.21	17.15	22.33	17.38	14.45	4.46	6.83	13.87	5.60

Table 2. Color variations of a normal tongue

Color Space	Before Calibrated		After Calibrated	
	Mean	STD	Mean	STD
R	0.4604	0.0439	0.6135	0.0339
G	0.4141	0.0323	0.4940	0.0288
B	0.4632	0.0492	0.5066	0.0288
H	0.2213	0.1103	0.3074	0.2669
S	0.1646	0.0337	0.2019	0.0190
V	0.4922	0.0387	0.1635	0.0339
L*	71.1732	2.0778	77.1573	1.7323
a*	4.7128	2.1826	7.1351	0.7140
b*	-3.3852	3.0458	1.3833	1.5716

Table 3. Texture feature representation experiment

Image	Entropy	Energy
1 (Cancer)	4.7513	0.0769
2 (Cancer)	4.2905	0.1407
3 (Cancer)	5.2012	0.0927
4 (Normal)	5.1716	0.2060
5 (Normal)	5.1329	0.3052

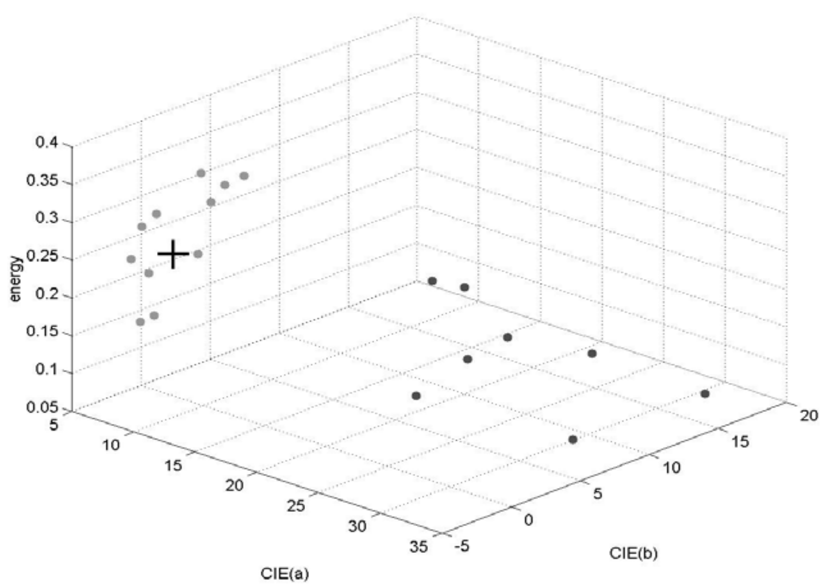

Figure 4. Classification Example: left set –cancerous, right set-healthy

1. *Color variations of a "normal" tongue*. We tested with 17 tongue images taken from a "healthy" individual with digital camera under different combinations of illumination and lighting orientations. The illumination conditions were daylight and indoor lighting in an office. 160 points from each tongue image were sampled to generate the data as shown at Table2.

2. *Texture Feature Representation.* We tested five images that contain two classes: "cancer" or "normal". We found that Energy Function is more sensitive to the data.

3. *Classification Model*. We use 3-D feature space to visualize the classification. The principal features are: energy function values (texture), a* and b* (color). Figure 4 shows a result of the classification based on 11 normal tongue images and 8 tongue images from patients with cancer. The "cancer" tongue images were digitized from publications that are lack of color calibration.

Discussions

The color check-board-based imaging method is simple but it needs extra efforts to calibrate the color and remove highlights and shadows. In addition, distance is a factor that has impact on texture classification.

Unfortunately, the original version of "Snake" only considers pixel intensity, which doesn't take advantage of the color information. We plan to expend the energy function that includes the color attributes.

Our next step is to collect more tongue images from those patients with G.I. cancers. We need to calibrate the model with more data and implement data mining algorithms.

Acknowledgement

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