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# A FAST AND EFFECTIVE SEGMENTATION ALGORITHM WITH AUTOMATIC REMOVAL OF INEFFECTIVE FEATURES ON TONGUE IMAGES

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## Abstract

In computerized tongue diagnostic system, tongue body color has been one of the essential features that contain rich information for diagnosing disease. However, tongue body color measurement can be influenced by the tongue coating color and other ineffective features such as significant coatings, shadows, teeth mark and crackles. This paper presents a fast processing segmentation algorithm using Hue, Saturation and Value (HSV) color space transformation to segment and remove these ineffective features aiming to have an accurate color measurement for online diagnosis. The newly devised Brightness Conformable Multiplier (BCM) has been proposed to automatically adjust the threshold brightness based on three conditions of lower perioral area's brightness, $V_{lower}$; when $V_{lower}$ is smaller than its standard deviation, $V_{lower}$ is greater than its standard deviation and otherwise. Besides, the Modified Sequential Algorithm (MSA) has been proposed to offer fast processing algorithm of 1.445 seconds and better segmentation. The successful segmentation rate was recorded as 90%. Furthermore, color measurement is carried out on the segmented samples and the analysis showed that the dispersion range of tongue body color measurement is small. This indicates a convincing result as the color boundary among light red, red and deep red tongue has been determined precisely.

*Keywords*: Kampo medicine, tongue diagnosis, segmentation algorithm, threshold brightness analysis, tongue color analysis

## Abstrak

Melalui sistem diagnostik berkomputer, warna badan lidah telah menjadi salah satu ciri-ciri penting yang mengandungi maklumat yang kaya untuk mendiagnosis penyakit. Walau bagaimanapun, pengukuran warna badan lidah boleh dipengaruhi oleh warna salutan lidah dan ciri-ciri lain yang tidak berkesan seperti salutan lidah yang ketara, bayang-bayang, tanda gigi dan rekahan. Kertas kerja ini membentangkan algoritma pemprosesan pantas dengan menggunakan Warna, Kepekatan dan Kecerahan (HSV) transformasi ruang warna untuk segmentasi dan membuang ciri-ciri yang tidak berkesan bertujuan untuk mendapatkan ukuran warna yang tepat untuk diagnosis atas talian. Pendarab Turutan Kecerahan (BCM) yang baru direka telah dicadangkan untuk melaraskan kecerahan ambang secara automatik berdasarkan tiga syarat kecerahan kawasan perioral rendah iaitu $V_{rendah}$; apabila $V_{rendah}$ lebih kecil daripada sisihan piawai, $V_{rendah}$ lebih besar daripada sisihan piawai dan selainnya. Selain itu, Algoritma Ubahsuai Berjujukan (MSA) telah dicadangkan untuk menawarkan pemprosesan masa yang lebih cepat iaitu 1.445 saat dan segmentasi yang lebih baik. Kadar segmentasi yang berjaya telah direkodkan sebagai 90%. Tambahan pula, pengukuran warna dijalankan ke atas sampel bersegmen dan analisis menunjukkan bahawa julat penyebaran pengukuran warna badan lidah adalah kecil. Ini menunjukkan hasil yang meyakinkan kerana sempadan warna antara lidah merah, lidah merah cerah dan lidah merah gelap telah dapat ditentukan dengan jitu.

*Kata kunci*: Perubatan kampo, diagnosis lidah, algoritma segmentasi, analisis kecerahan ambang, analisis warna lidah

## 1.0 INTRODUCTION

Over the decades, tongue images have been analysed in terms of their color, texture and geometry. In traditional East Asian Medicine, the examination of tongue features contributes to rich information in diagnosing diseases. In Traditional Japanese medicine (also called Kampo), there are several reported works to objectify the clinical findings with tongue feature information for diagnosis [1-9]. Kampo medicine is an alternative medicine in Japan which delivers a concept of preventive medicine with an early diagnosis to preserve the healthy culture life. The physicians or practitioners use tongue features such as color, moisture, shape, and unique textures to predict the patients' condition and disease-oriented state (known as Mibyou in Japanese) [2]. However, the process of observing the tongue features sometimes can be influenced by the illumination condition or subjectivities among practitioners. To rationalize the uncertainty and to create a healthy lifestyle with a computerized system in Kampo medicine, some clinical analyses employ intelligent image processing.

Medical imaging devices aim for immediate and accurate result, especially in diagnostic devices. There are several essential steps in computerized tongue diagnosis system, which include segmentation, color correction, feature extraction with analysis of color, texture and geometry, and classification of diseases. Nonetheless, the most significant step towards the computerized tongue diagnosis is the accurate, fast and robust segmentation algorithm procedure to distinguish tongue body from the perioral area, teeth, and lips. Segmentation procedure is a process of partitioning the image into multiple segments such that significant region can be identified to be researched on. Some of the techniques introduced currently in the market of computerized tongue diagnostic device are still experiencing the failure of segmentation in online procedures (on-the-spot diagnosis). Long execution time and false segmentation including the unnecessary features are the limitations of segmentation method. These limitations can affect the final image analysis drastically, particularly in color image analysis.

Many common segmentation methods have been applied in the field of computerized tongue diagnosis such as conventional edge detection method (Canny, Sobel)[10], threshold method[10-13], histogram method [11], hyperspectral image segmentation via spectral reflectance and wavelength [1, 14-17], Snake and Active Contour Method (ACM) [18-23] and J-Image Segmentation (JSEG) based Partition [24]. Geo-vector Flow (GVF) is actually part of ACM in doing curve evolution and there are some reported works on its efficiency in tongue diagnosis. ACM and GVF develop the convergence of energy that propagates to the real boundary using internal and external forces. In 2005, Bo Pang *et al.* [23] proposed a new improved method using the Bi-elliptical Deformable Contour (BEDC) to extract tongue body from the perioral area. They proposed BEDC as a combination of a Bi-elliptical Deformable Template (BEDT) and ACM. According to this paper, the automated tongue image segmentation is difficult due to two factors:

(a) There are many pathological details on the surface of the tongue that may affect the edge extraction.
(b) The shapes of the tongue bodies captured from various persons (with different diseases) are quite different, so prior initialization procedure is hard using predefined deformable template.

In conventional Snake model-based segmentation method, the use of rigid templates cannot produce satisfactory results in general. This realization had led to the use of deformable shape model in image segmentation. The BEDT captures gross shape features by using the steepest decent method on its energy function in the parameter space. The BEDC is derived from the BEDT by substituting template forces for classical internal forces, and can deform to fit local details. Nonetheless, this method requires very long execution time in order to calculate the edges and extract the tongue body from the background. In fact, this is not practical especially in online tongue diagnosis and future medical diagnosis prospect. In some cases, BEDC fails (4.7% of the 3572 samples) to find the correct tongue contour due to similar values on the red color plane especially around the tip of the tongue as the edges become very vague or even totally missing.

GVF Snake is limited to binary and gray scale images rather than color images [20]. The contours precision is also limited to pre-processing initial contour strategy [11]. Therefore, in 2007, researchers from China had proposed [20] color ACM to overcome these drawbacks. Even though they had introduced the knowledge-based technique to detect tongue body boundary via vertical projections and Sobel edge detection, the abundance steps causes the computational complexity despite the fact that the color analysis is more valuable. Some of the ACM and Snakes methods failed to eliminate shadows and other unwanted features that can affect color analysis for diagnosis. Recently, some researches have already improved the limitations of GVF by introducing the Double GVF [19, 25] where both upper and lower half boundaries of signed distance function speeded up the curve propagation respectively. This method is believed to outperform the accuracy of the conventional GVF of around 0.4% via True Positive Volume Fraction (TP) formula yet the execution time will be the demerit.

Threshold method is the simplest method in image segmentation analysis but the separation technique is limited to only significant distinguishable region of light and dark. The fundamental of threshold method is to select an optimal gray-level threshold value to separate the objects of interest (foreground) in an image from the background based on their gray-level dispersal. Several works have been reported as a stand-alone threshold method or hybrid of it [10-12]. In 2008, a novel algorithm for color tongue image segmentation based on Hue, Saturation, and Intensity (HSI) [13] was proposed to segment the color tongue image for tongue diagnosis purposes. The proposed segmentation based on HSI space applied the threshold values of hue and intensity components to extract the foreground (tongue body) from the perioral area (lips, teeth as well as cheek). The proposed conventional sequential algorithm had two nested loops that mark the connected area to determine the tongue body as the biggest blobs apart from the left pixel from the surrounding area after threshold procedures. However, we had identified that the nested loops need to be reduced. To overcome this limitation, we proposed MSA which uses only single scan loop to calculate the maximum connecting area which is tongue body in the image. In some cases, threshold method can be implemented to separate the tongue coating from the substance and also to detect valuable texture on the substance area but the performance degrades when the global distribution of target image and background vary widely over the samples.

Hyperspectral imaging has been one of the popular methods to attain the tongue information via spectral response extraction of several image cubes. In remote sensing application, hyperspectral imaging has been established since 1984. The method takes into account the knowledge of electromagnetic energy where all materials reflect, absorb, and emit energy, at specific wavelengths with exclusive patterns depending on their molecular composition[15]. In tongue diagnosis, some previous works [1, 14-17] had utilized the spectral reflectance and wavelength of hyperspectral imagery cubes differences to segment the tongue as well as coating area from the background. The principal of hyperspectral imaging is straight forward and it contains not only the whole information of RGB channel but also some hidden information that some of the RGB image does not have. The features of each image can be regarded as black and white images collected from red, green, and blue lights and can be divided based on their spectral range corresponding to its true color in RGB space. Nevertheless, this system produce some limitations such as the high cost of the hyperspectral camera and long processing time per frame that exacerbates the difficulties of patients to posturize their tongue for several seconds.

The latest reported works in 2014 [11] proposed a new algorithm on iterative back projection system using histogram and Learning Based Digital Matting (LBDM) to segment the tongue images. The process of segmentation implements the normal features training to extract tongue features and model training using Cascaded of Boosted Classifiers for Rapid Object Detection to locate the tongue. The back projection for tongue body detection is an iterative process to produce a probabilistic image sample and extract the current possible substance location as new sample region. After the back projection converges, a tri-map will be generated to label the foreground and background before it can be used in parallel with the LBDM algorithm to finally segment the tongue body based on this label. Such knowledge-based information segmentation method has become sophisticated yet complicated as it always requires prior knowledge such as color distribution, region size information, and initial approximate location of the tongue body [11, 18, 22].

The newly proposed segmentation algorithm is devised to overcome the limitations of the previous algorithm such as undetectable vague edges, irremovable shadows and other unwanted features on segmented tongue body, imperfect segmentation due to poor convergence to boundary concavities and long execution time with complex system. These unwanted features will definitely have distinctive tri-stimulus color values that can significantly affect the result of color analysis and final diagnosis. High accuracy of segmentation results and quantitative measurement among each tongue color clusters revealed that the proposed algorithm is feasible and promising for future computerized tongue image processing.

## 2.0 PROPOSED ALGORITHM

### 2.1 HSV Color Space Analysis

Tongue features accumulated complex information in terms of its texture and color. Posturizing tongue for more than few seconds may affect the outcomes of tongue color analysis [4]. In order to analyze the tongue body measurement without ineffective features (such as crackles, significant coating, shadows, and teeth mark) that may affect the diagnosis result, a non-complex algorithm using Image Segmentation Based on HSV color space and Gaussian smoothing with threshold was proposed. HSV was used because the color space is more intuitive and perceptually relevant than Cartesian representation such as RGB. The Hue is expressed as an angle around a color hexagon mainly using the real axis as 0° axis. The Value component $V$ is measured along the cone and has two different conditions. If $V = 0$, the color represented is black and if $V = 1$ the color represented is white [26]. The Saturation is the purity of the color and is measured as the distance from the $V$ axis looking at the hue, saturation and value hexagonal cone as illustrated in Figure 1.

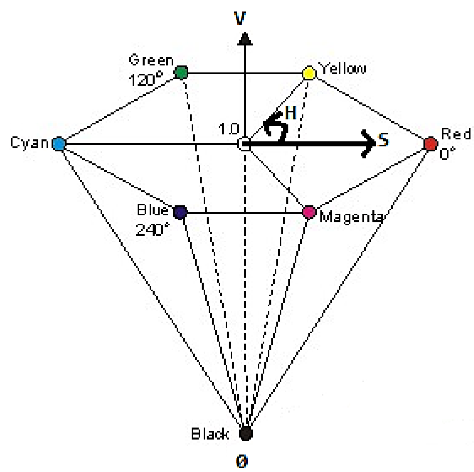



**Figure 1** HSV coordinate system

In computer visions, HSV space tries to capture the components as the way humans perceive color and interpret the actual color components like brightness and intensity of the color. RGB color space has no intrinsic relation to the natural color properties, neither to human interpretation. Moreover, HSV separates the brightness, or the image intensity, from Chroma or the color information. This is the most important value in our task to separate the tongue body from the perioral area as tongue body's brightness is distinguishable. Meanwhile, its robustness to lighting changes is another merit of HSV space. The advantage of implementing brightness, $V$ value of the HSV space can be interpreted in Figure 2 and Figure 3 respectively. Two histograms that were using brightness, V for the perioral area and tongue body area had been investigated. Looking at both figures (Figure 2 and Figure 3), the histogram peak near 0 to 0.1 is the background image and can be neglected. By using our tongue image samples, it had been proved that the position of perioral's pixel area were determined around $V = 0.9$ to $V = 1$ while the tongue body's pixel area were located around $V = 0.6$ to $V = 0.8$. In other words, there are no overlapping histogram pixels detected between perioral area and tongue body area by using brightness, V attribute. This finding had revealed the appropriateness of choosing V as a threshold variable to separate the tongue body and perioral area impeccably.

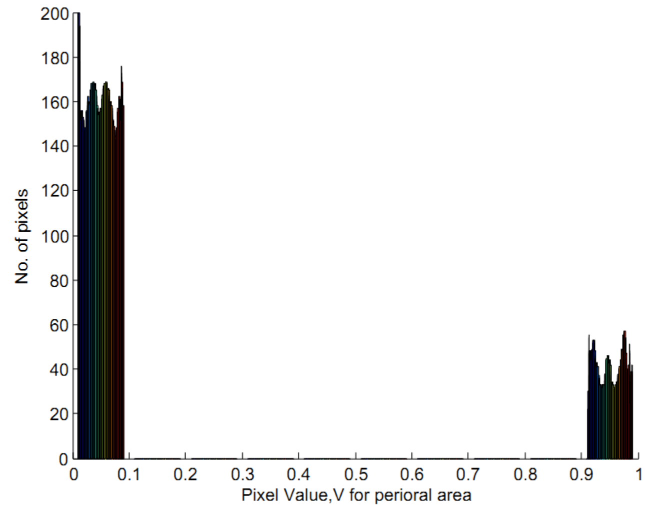



**Figure 2** Histogram of perioral area of Value (V) from HSV color space

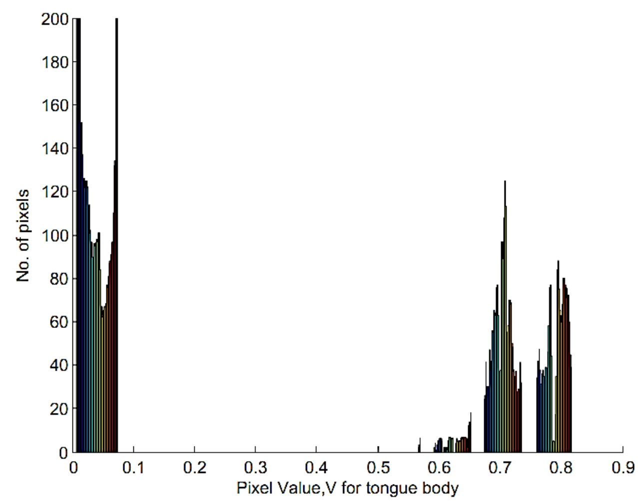



**Figure 3** Histogram of tongue body of Value (V) from HSV color space

## 2.2 Brightness Selection with Boundary Conformable Multiplier (BCM)

The threshold method by Sawabe *et al*. [27] was inspired to pre-classify the image between foreground and background using grayscale images. Similarly, Sawabe's threshold method could be employed in color image represented in HSV color space whereby one of the color components can be used as a threshold variable. By using integrating sphere and standard illumination specification, the brightness uniformity on only tongue body area can be properly realized and this makes the tongue body distinguishable from the perioral area. In other words, tongue's body area is supposed to obtain more brightness from the illuminance compared to the perioral area. With our setup, the threshold method proposed here was based on the brightness whereby

Value component of HSV was used as the threshold variable. $V$ is formulated as in (1):

$$V = \frac{max\{R, G, B\}}{255} \tag{1}$$

Next, upper threshold brightness, $V_{upper}$ and lower threshold brightness, $V_{lower}$ of $V$ were determined to recognize the tongue body area and perioral area are expressed in (2) and (3) respectively:

$$V_{upper} = V_m + \sigma \tag{2}$$

$$V_{lower} = V_m - \sigma \tag{3}$$

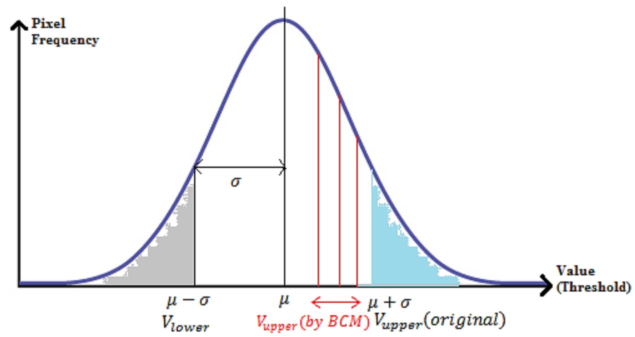
where $V_m$ is the average value of $V$ in HSV of the tongue image and $\sigma$ is the standard deviation of $V$. Using such threshold method, those pixels with $V_i \geq V_{upper}$ were recognized as tongue body whereas those lower or equal to $V_{lower}$ were recognized as perioral area. However, the safe gap between $V_{upper}$ and $V_{lower}$ that allows the differentiation between tongue body and perioral area may vary according to the illumination exposure on a tongue body and perioral area. Although the experiment set up focused mostly on the illuminance on the tongue body, brightness obtained by the tongue body area may vary subject to the patients' posturing. In short, the tongue body may not always acquire perfect lighting compared to the surrounding. Based on this fact and our observation on the captured tongue images, we introduced a multiplier called Boundary Conformable Multiplier (BCM), $\varepsilon$ into the upper threshold brightness equation as in (4):

$$V_{upper} = V_m + \varepsilon.\sigma \tag{4}$$

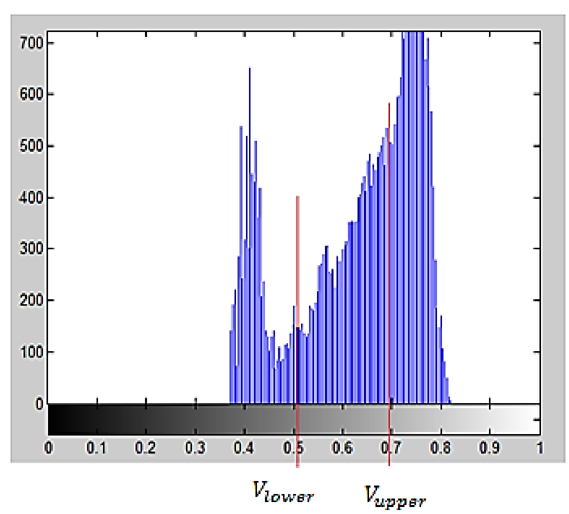
BCM or $\varepsilon$ is formulated to adjust $V_{upper}$ based on $V_{lower}$ or the brightness for perioral area based on three conditions as shown as follows in (5):

$$\varepsilon = \begin{cases} V_m & if\ V_{lower} < 2\sigma \\ V_{min}(V_1, V_2 \dots V_N) & if\ V_{lower} > 2\sigma \\ {V_m}^2 & otherwise \end{cases} \tag{5}$$

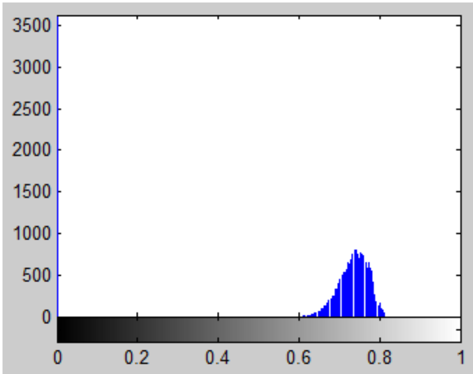
where $0 \leq \varepsilon \leq 1$ and $(V_1, V_2 \dots V_N)$is the brightness value $V_i$ for each pixel. Looking at the image processing perspective of segmentation, the newly developed threshold method was devised to discriminate between the foreground (tongue body) and background (perioral area including teeth) using $V_{lower}$ and $V_{upper}$ as shown in the histogram of brightness attribute, $V$ in Figure 4(b). Using histogram, an ideal image can be described as having a normal distribution function of histogram. In tongue image acquisition device, brightness component may vary across a perioral area and tongue body due to ambient lighting or illumination condition of the device. Thus, the inconsistent histogram pattern distribution of tongue images makes it difficult to segment the image using conventional threshold concept. To overcome this limitation, $V_{upper}$ can be shifted accordingly using newly developed BCM based on the information of the lower threshold brightness and the standard deviation, $\sigma$ of the system to detect the tongue body. The BCM conditions based on Gaussian distribution concept and segmented tongue histogram are shown in Figure 4(a) and Figure 4(c). Figure 4(b) represents the whole raw data sampling pixels histogram before Gaussian Smoothing process. The $V_{upper}$ as in (2) was modified to compensate the threshold boundary adjustment towards elimination of ineffective region on tongue body and compromise certain significant brightness to exclusively segment the tongue body. By measuring the actual brightness value of those ineffective features such as crackles, teeth mark and significant coating, it was proven that those ineffective features lie on the safe gap between $V_{lower}$ and $V_{upper}$ of the histogram. The transitional brightness boundary allows the brightness safe gap to be adjustable to well represent the ineffective features according to brightness change. This situation makes those unwanted features pixels that rely on the safe gap region were properly removed. On the other hand, the distinctive pixels of shadows candidate can be easily eliminated using Gaussian Smoothing technique.



(a)



(b)




(c)

**Figure 4** (a) BCM concept of threshold transition (b) Histogram of tongue image before segmentation (c) Final segmented tongue image histogram

The computational process is equivalent to the first image smoothing by convolving it with a Gaussian kernel. Finally, Modified Sequential Algorithm (MSA) was employed to obtain the largest connected area (tongue body) and to remove unnecessary remaining regions after the threshold process. The proposed algorithm flowchart and MSA flowchart are shown in Figure 5 and Figure 6.

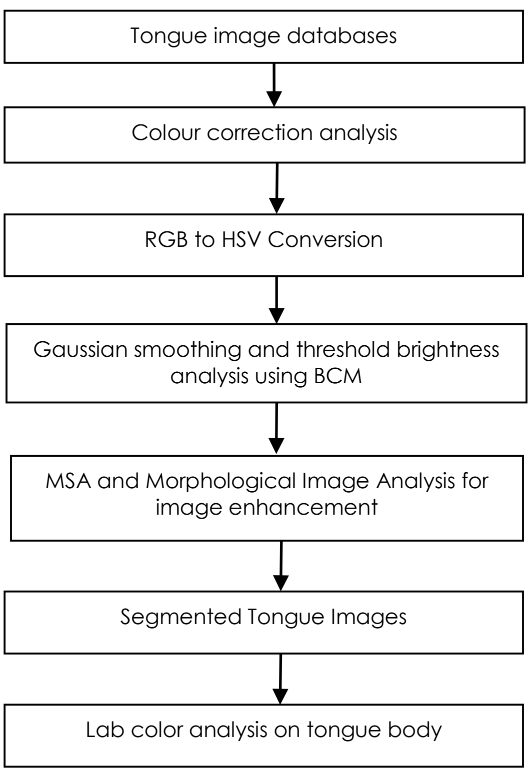



**Figure 5** Proposed work flowchart

The image label that has the maximum pixel label can be regarded as tongue body and other smaller labelled patches can be removed from the background. The overall stages of our proposed method and quantitative measurement can be summarized in Figure 6.

## 3.0 TONGUE DATABASES SPECIFICATION

Tongue images were taken by Tongue Image Analyzing System (TIAS) on hundreds of outpatients in Oriental Medicine Research Centre, Kitasato University in Japan. These pictures have been used for segmentation and color evaluation of tongue body. The implemented elements in TIAS are as follows:

(a) Halogen lamp for illumination to acquire adequate tongue color information.
(b) Integrating sphere.
(c) 1280x1024 pixels high-speed Charged Couple Digital (CCD) camera to capture high-resolution 24bit RGB (redness, greenness, blueness) tongue images.
(d) 24 color chart for color correction purposes.

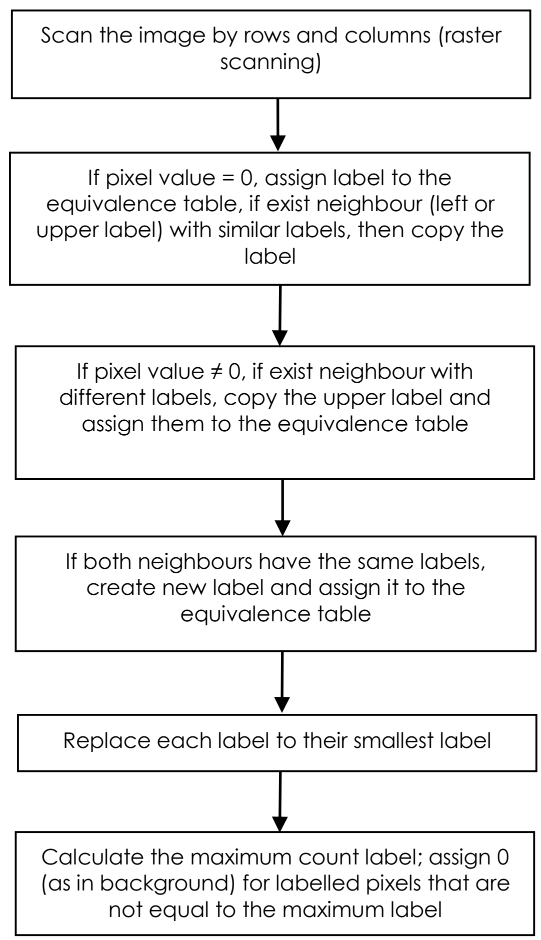



**Figure 6** MSA flowchart

The tongue pictures were taken within a few seconds after protrusion. This procedure prevents the darkening tongue color portion caused by blood congestion which begins within a few seconds after protrusion and will affect the original color of a tongue

[4]. From 300 images, only 90 images of very thin to non-coating tongue images were taken as samples to measure the tongue body color because coating with moderate or high thickness will strongly affect the average color analysis of tongue body. Acquired tongue pictures were classified into three color types (light red, red, and deep red) according to a clinical diagnosis made by nine practitioners who have experiences of Kampo medicine for more than five years.

## 4.0 EXPERIMENT RESULTS AND DISCUSSION

### 4.1 Segmentation Result: Ineffective Features Detection and Removal for Tongue Body Color Objectification

For steadfast analysis, all image samples had undergone color correction process to produce high color reproducibility and to improve the color inconstancy. In order to have better diagnosis result, most of the researchers take into account color correction as an essential part in the pre-processing steps prior to the detection of the diseases [28-32]. The analysis of whole tongue body color had been carried out using the resulting images from the segmentation algorithm. Ideally, this proposed fast and effective segmentation algorithm is a combination technique that offers the segmentation procedure as well as the detection and elimination of several ineffective tongue features to accurately analyze the substance color. This algorithm has an execution time (MATLAB environment with intel ® Core™ i7-3820CPU @3.60GHz) around 1.445 seconds to analyze 60,000 pixel of images, which is very promising and convincing for online testing and the development of robust algorithm for future application of diagnostic medical devices. The resulted images after segmentation and ineffective features removal aiming to have a perfect quantification of a tongue substance are shown in Figures 7-10 accordingly.

As shown in the resulted images, crackles, teeth mark, shadows, and significant color coating had been removed successfully to produce a more reliable result in substance color analysis. The significant color change from the ineffective features on tongue body has to be eliminated as they can really influence the end result analysis especially the color measurement. Most of the segmentation methods nowadays require another algorithm to perfectly remove those entire features that makes the runtime higher and more effort needed. This algorithm had perfectly removed all those significant features and regions on the images that have clear pixel distinction of those features with the background (tongue body) after segmentation was done. The segmentation efficiency was confirmed by the quantitative measurement to predict the color threshold between three tongue body color groups which were light red, red and deep red.


**Figure 7** Teeth mark elimination


**Figure 8** Crackles elimination

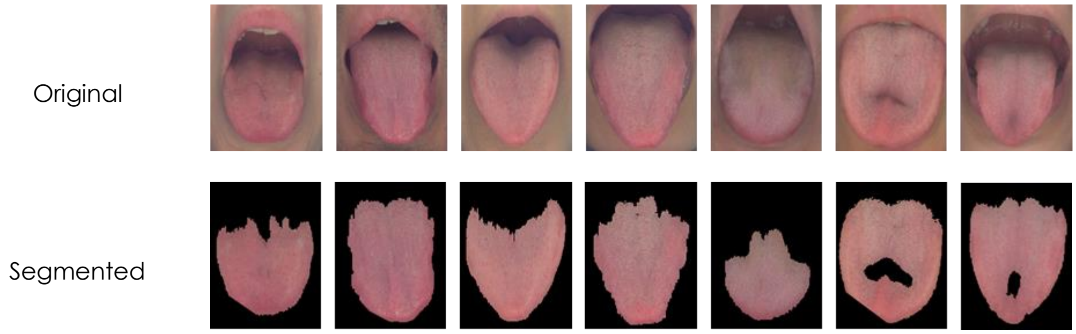



**Figure 9** Significant coating elimination


**Figure 10** Shadows elimination

## 4.2 Tongue Body Color Measurement

Over hundreds of images taken by TIAS, the best tongue pictures around 300 images were chosen. These images were taken with only a few seconds duration after patient posturize their tongue to maintain the color consistency of tongue images. For this analysis, the best 90 images corresponding to the three clusters of light red, red and deep red within very thin to non-coating tongue images had been selected. These selected images had undergone the proposed segmentation algorithm beforehand. Very thin to non-coating images were employed to provide an ideal measurement of tongue body color without being influenced by the coating color even after the segmentation with coating removal procedures. Tongue body is also known as a substance for several researchers and practitioners. Even though the sample size were not so large, the precision of the resulted segmented images with those unwanted features removal delivered promising measurement results. The color measurements had provided small dispersion around the mean value for every tongue color group.

This promising resulted pattern clearly separated each tongue body color group though they might be small overlapping cluster range. The overlapping pixels are due to several factors such as:

(a) Tongue clusters had been subjectively separated by several practitioners.
(b) One tongue image might comprises of more than two color differences such as red, deep red and light red in a different region on tongue body.
(c) Because the color gamut of the tongue is relatively narrow [33], the overlapping pixels might occur between color groups.

After segmentation, the average Lab color values for each cluster (light red, red and deep red tongue) were calculated and the results are tabulated in Table 1.

**Table 1** *CIELab* color analysis for segmented tongue body

| **Tongue Cluster/ *CIELab* color** | $L$ | $a$ | $b$ |
|---|---|---|---|
| light red cluster (n=30) | 59.36±1.62 | 25.78±2.50 | 12.15±2.57 |
| red cluster (n=30) | 52.14±2.40 | 29.87±2.46 | 9.65±2.18 |
| deep red cluster (n=30) | 50.16±2.65 | 24.38±2.00 | 6.09±1.54 |

Here, color opponent space, *CIELab* was implemented to distinguish between the findings of luminance, $L$ and the chromaticity component (solid color component with a fixed lightness) $a$ and $b$ for perceptual uniformity. The color boundary between each cluster for future computerized diagnosis that based on color pattern distribution was presented. The clearly distinguishable color patterns of light red, red and deep red tongue color clusters indicate a reasonable result even though the tongue color gamut was very narrow. These results indicate high precision segmentation algorithm by ineffective features elimination on tongue body for tongue body color analysis.

The luminance component $L$ in deep red tongue had provided the least luminosity value compared to red and light red. The chromatic component $a$ had the highest value in red clusters and $b$ component had the highest value in light red clusters. According to the state-of-the-art of *CIELab* color space, the farther $a$ and $b$ components from 0, the more color it gets. In $a$, red component is located in the positive direction. Therefore, we had the highest pixels value of $a$ in red tongue cluster. Nevertheless, for $b$ component, the yellow pixels located in the positive direction and blue being in the negative direction. By looking at the CIE 1931 color space chromaticity diagram where *CIELab* space was invented, light red has least range of wavelength distance compared to yellow. Being the most influenced region compared to the other two clusters is the reason of $b$ component being the highest in the light red cluster. The distributions of only chromaticity pixels and Lab space pattern are shown in Figure 11 and Figure 12. The precise quantitative measurement of the tongue body color with their color evidence discrimination delivers the successfulness of the segmentation method and the feasibility to produce the tongue body color boundary discrimination for future diagnosis.

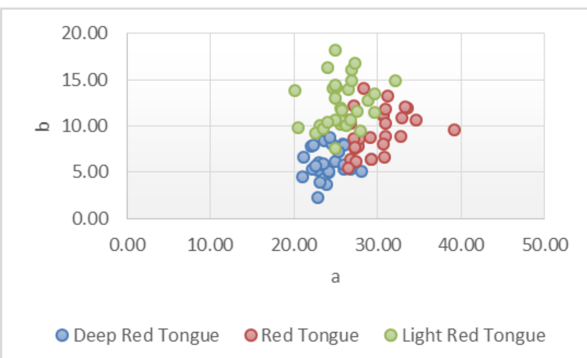



**Figure 11** Chromaticity discrimination pattern among clusters

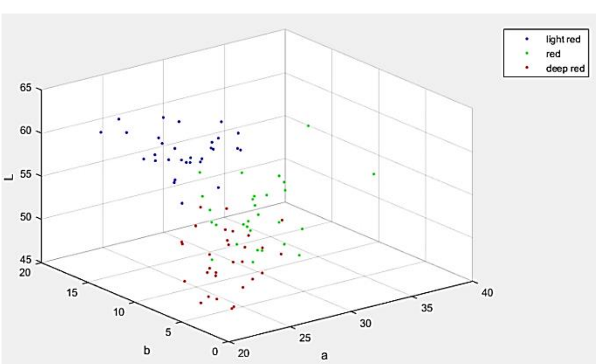



**Figure 12** *Lab* color pixels distribution among clusters

## 4.3 Performance Analysis

The accuracy of our proposed segmentation with ineffective features removal was verified using the labeled data confirmed by several practitioners in Oriental Medicine Research Center, Kitasato University, Japan. These labeled images were made from nine practitioners who have experiences of Kampo medicine for more than five years. The practitioners' evaluation environment with their naked eyes was under 5500K color temperature fluorescent light in outpatient ward. Only similar labeled data verified by at least two practitioners had been adopted to confirm high reliability and accuracy of these data. The successful segmentation rate recorded was around 90%. The successful segmentation rate was measured as in (6):

$$\frac{number\ of\ successful\ segmented\ images\ with\ ineffective\ features\ removal}{total\ number\ of\ image\ samples}\ x\ 100 \quad (6)$$

Furthermore, the effectiveness of our algorithm could be measured by comparing the average *CIELab* color parameters of tongue body after segmentation using our proposed algorithm which is equipped with shadow removal function. The comparison of average color measurement between our proposed algorithm and ACM algorithm are tabulated in Table 2 which showed very significant differences that can affect the final diagnosis. This is because the tongue color gamut is very narrow. Only small differences in color measurement will lead to inaccurate color diagnosis. Therefore, an accurate segmentation procedure is vital for an accurate diagnosis.

**Table 2** *CIELab* color difference after shadow removal

| Method/Average color | $L$ | $a$ | $b$ |
|---|---|---|---|
| Active Contour Method (ACM) (without shadow removal)-using image #1 | 46.0152 | 25.048 | 9.428 |
| Our proposed segmentation (with shadow removal)-using image #1 | 47.2867 | 26.757 | 10.5007 |

Additionally, the execution time of our proposed algorithm was recorded and compared with three other methods as shown in Table 3. This comparison revealed that our proposed segmentation is fast enough for future online tongue diagnosis system. These algorithms were executed in MATLAB using similar image specifications (60,000 pixels image) and system performances (intel®Core™, i7-3820CPU @3.60GHz).

**Table 3** Execution time and performance comparison

| Method/Performance | Execution time (seconds) | Ineffective features removal |
|---|---|---|
| Histogram-based segmentation method [11] | 2.84 | No |
| Snake or Local ACM [18] [20] [22] | 10.06 | No |
| Improved ACM [19][23][25] | 4.05 | No |
| Our proposed segmentation | 1.445 | Yes |

## 5.0 CONCLUSION

There are many previous type of research in computerized tongue diagnostic system but the objectifications of tongue findings and related matters are still in progress to achieve better solutions, performances as well as device optimizations. Therefore, in order to objectify the valuable information of traditional East Asian medicine as a complimentary medicine, it is necessary to build an automated system with quantitative measurement standard for tongue diagnosis and explore the feature-disease relationship. Towards this objectification, color measurement on tongue body can accumulate very valuable information. The ineffective features remained in some segmented tongue images will strongly affect the color analysis and diagnosis. This proposed segmentation had improved some of the previous researches in [18, 19, 21, 33] by eliminating the unwanted features like shadows.

The novelty of our research relies on the proposed multi-functional segmentation algorithm with automatic alteration of brightness threshold using BCM to segment the tongue body and eliminate its ineffective features. The developed segmentation system achieved 1.445 seconds of processing time using 60,000 pixels of the test image which is very fast and suitable for online diagnosis and the resulted segmentation with an elimination of ineffective features (Figures 7-10) for accurate color measurement are favorable for accurate objectification on tongue diagnosis. The successful segmentation rate was recorded as 90% compared to the labeled data determined by the practitioners beforehand. The quantitative analysis to objectify the tongue body color analysis has verified the efficiency of the segmentation algorithm by showing the reliable result with small dispersion measurement (Table 1) and clear separation of the color boundary between clusters (Figures 11-12). As discussed earlier, the specification of the computerized tongue machine may affect the image outcome and the brightness condition as well. Similar or smaller distinguishable brightness of perioral and tongue body area may result in difficulties of automatic transition by BCM. Once the limitation of the tongue acquisition device specifications can be improved especially on the illumination condition uniformity with an appropriate light source, the proposed work can work reliably well.

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