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SVR BASED COLOR CALIBRATION FOR TONGUE IMAGE

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Abstract:

Tongue color is one of the most important pathological features for Computer Aided Tongue Diagnosis System (CATDS). Color distortion of tongue image, which is often caused by the inconstancy of lighting conditions, can seriously affect the validity of diagnosis results obtained by CATDS and furthermore, impair the interchangeability among tongue images captured by different devices. To circumvent the above problems, we present a novel color calibration model based on Support Vector Regression (SVR) method in this paper. First, a new colorchecker which provides a suitable reference for the following color calibration is produced by color clustering of 322 tongue images. Then, a comparative analysis between the SVR based color calibration method and Polynomial Regression based one is carried out. Results indicate that SVR based color calibration model, cooperating with the proposed colorchecker, provides an outstanding calibration effect and plays an important part in the image acquisition of CATDS.

Keywords:

Color calibration; tongue diagnosis; SVR; polynomial regress

1. Introduction

For thousands of years, tongue diagnosis [1], [2] has been one of the most important and widely used diagnosis methods in Traditional Chinese Medicine (TCM). By examining the tongue, the main pathological process of complex disorder in the internal organs of human body can be instantly clarified. Therefore, it is of great value in today's clinical diagnosis and physical examination. However, due to its drawbacks in quantification and standardization, the development of tongue diagnosis is, to a certain degree, stagnated in modern times. To develop Computer Aided Tongue Diagnosis System (CATDS) is generally considered as an efficient way to accelerate the modernization of traditional tongue diagnosis [3].

For CATDS, the colors of tongue image are often distorted because of the inconstancy of lighting conditions (lighting geometry and illuminant color) and difference of optical characteristics of capturing devices. The human visual system can compensate for an overall color distortion in a scene caused by a colored light source, while most CATDSs do not possess such ability even though they can provide white balance functions which are helpful for color fidelity of tongue images. As a result, during color based diagnosis processing, images of the same tongue captured under different lighting conditions can be often classified into different classes, which often leads to inaccuracy of tongue color analysis and consequently, damages to the validity of final diagnosis results. Moreover, the interchangeability between tongue images obtained by different acquisition devices is also impaired for the same reason, so that it is difficult to share the images for different researchers. Therefore, further calibration on the colors of tongue images is necessary for tongue image acquisition.

In [4], a Trigonal Pyramid (TP) color reproduce method is carried out. Without any colorchecker for reference, his method lacks enough objectivity. To compensate the errors in lighting, camera angle and color representation in the imaging system, the current color calibration method tends to use an embedded color check-board. Yang Cai's system [5] adopts Munsell colorchecker and a linear color calibration model to recover the original colors of tongue image under various lighting conditions. However, due to its inherent limitations, linear model can not obtain satisfied calibration result. Y. G. Wang, et al. [6] use polynomial regression based method. However, the above literatures do not provide any explicit definition of the colorchecker which is suitable for tongue color calibration, nor do they study on objective evaluation of the calibration result in tongue diagnosis practice. In this paper, a novel color calibration method based on Support Vector Regression (SVR) is proposed to calibrate color distortion of tongue image captured under different lighting conditions, as well as a new colorchecker which is suitable as the reference for tongue color calibration is provided by color clustering from 332 tongue images.

2. Colorchecker

To provide a proper color reference to calibration model, the cells of colorchecker must be close to the color of object to be calibrated. Since the colors of tongue images are more concentrated comparing to other nature objects, general colorcheckers, such as Macbeth, etc., are not suitable for tongue color calibration. Therefore, we adopt C.H. Li's regularized color clustering algorithm [7] to produce the color codes of the new colorchecker. First, 322 tongue images are used for the cluster algorithm, among which 202 images are captured from 202 healthy people, while the rest 120 images are from patients suffering from different diseases. Second, tongue surfaces are segmented from images and then each of them is divided into 32×32 square cells. By calculating means of colors in each cell, we get 99072 data for clustering. Finally, 24 color values are obtained by clustering. Moreover, in order to compare the difference of calibrations using different color codes, we also combine standard 24 color values provided by Microsoft Windows, the cluster values from [7] and gray values into the colorchecker. The whole check-board is composed of 4 kinds of colorcheckers as shown in Figure 1.

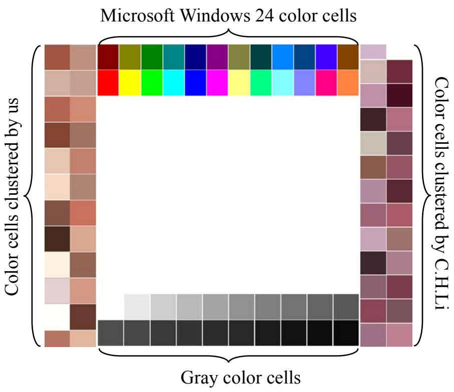


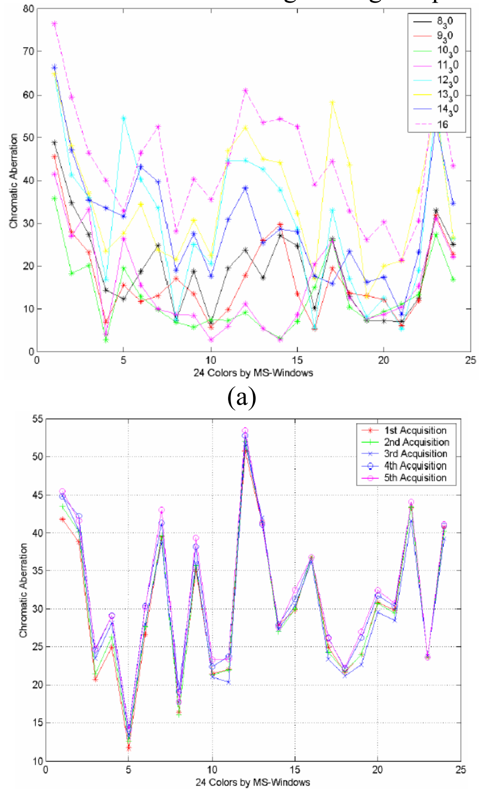
Figure 1. Combined Colorchecker

3. Tongue image acquisition

Traditional tongue diagnosis in TCM is commonly carried out under daylight and without any prevention from external lighting interferences. Figure 2(a) is color variations of the same colorchecker under daylight from 8:30 to 16:00 of the same day. Each curve represents the chromatic aberrations between cells values captured under nature lighting conditions and their measured value. In this diagram, the chromatic aberrations are calculated in CIELAB color space by

$$\Delta E^* = \sqrt{(\Delta L^*)^2 + (\Delta a^*)^2 + (\Delta b^*)^2}. \quad (1)$$

As shown in Figure 2 (a), there is obviously lighting fluctuation for nature daylight. Due to the poor stability of day-lighting condition, it can not meet the needs of tongue image acquisition for CATDS. Therefore, it is necessary to build a stable environment for tongue image acquisition.



(a)

(b)

Figure 2. Color variations under (a) daylight and (b) standard environment

We deliberately choose a Sony 900E video camera as the image capture device, which has a new type 3CCD kernel and therefore has relatively less distortion compared with others. This camera provides maximum 720×576 pixels with good white balance function, 50dB S/N ratio, as well as both PAL and NTSC signal. The light source acquisition device is a 250W cold-light type halogen lamp with 4800k colors temperature. To compensate the high hit emitting, we used optical fiber as wave guide and installed the light source separated from the image acquire part. The tongue image acquisition process is carried out within a darkroom to avoid external interference. As Figure 2(b) shows, the color variations of the same colorchecker obtained by the equipment are quietly consistent, so the developed acquisition equipment can provide a stable environment for tongue. This equipment is also approved by TCM expert and furthermore a Chinese Invention patent

(N0. 021324581). Owing to its stability, in this paper the term standard environment will refer to the environment provided by this equipment.

4. Preprocessing of color cells

Because of diffuse reflection caused by the material of colorchecker, there are more or less white noises on some color cells of the check-board. So a simple cluster based on Nearest Neighbor Clustering was adopted to calculate the color values of each cell. Figure 3 shows the color cells before and after preprocessing. All values of color cells in colorchecker mentioned in the following parts of the paper are obtained after this preprocessing.

Figure 3. Contrast of color value of cells:
Fist line: color cells before preprocessing;
Second line: color cells after preprocessing.

5. Polynomial regression based calibration

Give a set of data $\{(X_i, Y_i) \in R^N, i = 1,2,3,\cdots,N\}$, where X_i is the color value of a pixel in tongue image captured in unstable environment, Y_i is that of standard environment, and N is the number of total image pixels, there exists a function $F(\cdot)$, which can map X_i to Y_i. Therefore, color calibration can be described as a regression using $f(\cdot)$ to fit $F(\cdot)$ only by the n color values of colorchecker in the image to be calibrated, $\{(x_i, y_i) \in R^N, i = 1,2,3,\cdots,n\}$.

Let X^i_{std}, Y^i_{std} and Z^i_{std} be the CIELab values of ith color cells of the colorchecker obtained in standard environment, and X^i_{oth}, Y^i_{oth} and Z^i_{oth} be those of other environment to be calibrated, where $i = 1,2,3,\cdots,n$, and n is the number of cells in the colorchecker used in calibration. The polynomial regression model is given by

$$M_{std} = A^T \cdot V_{\ell n} \tag{2}$$

where

$$M_{Std} = \begin{bmatrix} X^1_{std} & X^2_{std} & \cdots & X^n_{std} \\ Y^1_{std} & Y^2_{std} & \cdots & Y^n_{std} \\ Z^1_{std} & Z^2_{std} & \cdots & Z^n_{std} \end{bmatrix}, \tag{3}$$

$$A = \begin{bmatrix} a_{11} & a_{21} & a_{31} \\ a_{12} & a_{22} & a_{32} \\ \vdots & \vdots & \vdots \\ a_{1j} & a_{2j} & a_{3j} \end{bmatrix} \tag{4}$$

is the transform matrix and

$$V_{\ell n} = \begin{bmatrix} v_{11} & v_{12} & v_{13} & \cdots & v_{1n} \\ v_{21} & v_{22} & v_{23} & \cdots & v_{2n} \\ v_{31} & v_{32} & v_{33} & \cdots & v_{3n} \\ \vdots & \vdots & \vdots & & \vdots \\ v_{\ell 1} & v_{\ell 2} & v_{\ell 3} & \cdots & v_{\ell n} \end{bmatrix} \tag{5}$$

is a $\ell \times n$ matrix which is composed of X^i_{oth}, Y^i_{oth} and Z^i_{oth} with polynomial forms, where ℓ is number of polynomial terms. For instance, if ℓ =3, the terms are $\{X, Y, Z\}$, so the regression model becomes linear.

The solution of A can be gained by using least square method. All color values of the original image can be organized in the form of $V_{\ell n}$, and then the calibrated image can be calculated by (2).

6. SVR based calibration

Support Vector Machines (SVMs) developed by Vapnik [8], due to many attractive features and promising empirical performance, have been widely used to solve the classification problem and recently extended to address regression problems. Similarly to SVM, SVR also uses a nonlinear kernel to transform the training data into a high dimensional feature space where linear regression can be performed. The nonlinear SVR solution, using an ε-insensitive loss function

$$L_\varepsilon(y) = \max(0, |f(x) - y| - \varepsilon) \tag{6}$$

and Gaussian RBF kernel with the form,

$$K(\vec{x}_i, \vec{x}_j) = \exp\left(- \frac{(\vec{x}_i - \vec{x}_j)^2}{2\sigma^2} \right). \tag{7}$$

is given by

$$\max_{\alpha,\alpha^*} W(\alpha, \alpha^*) = \max_{\alpha,\alpha^*} \left\{ \begin{array}{l} -\frac{1}{2} \sum_{i=1}^{l} \sum_{j=1}^{l} (\alpha_i - \alpha_i^*)(\alpha_j - \alpha_j^*) K(\overrightarrow{x_i}, \overrightarrow{x_j}) \\ + \sum_{i=1}^{l} \alpha_i^*(y_i - \varepsilon) - \alpha_i(y_i + \varepsilon) \end{array} \right\}, \tag{8}$$

subject to the conditions,

$$0 \le \alpha_i \le C, i = 1,2,\cdots,l \qquad (9)$$

$$0 \le \alpha_i^* \le C, i = 1,2,\cdots,l \qquad (10)$$

$$\sum_{i=1}^{l}(\alpha_i - \alpha_i^*) = 0 \cdot \qquad (11)$$

Solving equation (8) with constraints (9), (10) and (11), determines the Lagrange multipliers $\overline{\alpha_i}\overline{\alpha_i^*}$. With *Karush-Kuhn-Tucher* (KTT) conditions, the satisfied solutions are,

$$\overline{\alpha_i}\overline{\alpha_i^*} = 0, i = 1,2,\cdots,l, \qquad (12)$$

Therefore, the support vectors are exactly the points where Lagrange multipliers are greater than zero. The regression function is given by

$$f(x) = \sum_{SVs}(\overline{\alpha_i} - \overline{\alpha_i^*})K(\vec{x}_i, \vec{x}) + \overline{b} \qquad (13)$$

where

$$\vec{w} \cdot \vec{x} = \sum_{SVs}\left(\overline{\alpha_i} - \overline{\alpha_i^*}\right)K(\vec{x}_i, \vec{x}), \qquad (14)$$

$$\overline{b} = -\frac{1}{2}\sum_{SVs}\left(\overline{\alpha_i} - \overline{\alpha_i^*}\right)\left[K\left(\vec{x}_r, \vec{x}_i\right) + K\left(\vec{x}_s, \vec{x}_i\right)\right]. \qquad (15)$$

For SVR based color calibration, L_{oth}^i, a_{oth}^i and b_{oth}^i represent the CIELab values of i th pixel of the image captured in other environment, where $i = 1,2,3,\cdots,N$ and N is the total pixel number of the image. The calibrate function $f(\cdot)$ is obtained by SVR regression model, which only refers to the color values of the colorchecker captured in standard environment, L_{std}^i, a_{std}^i and b_{std}^i, where $j = 1,2,3,\cdots,n$ and n is the number of cells. The Lab values of calibrated image obtained by SVR based color calibration model are given by

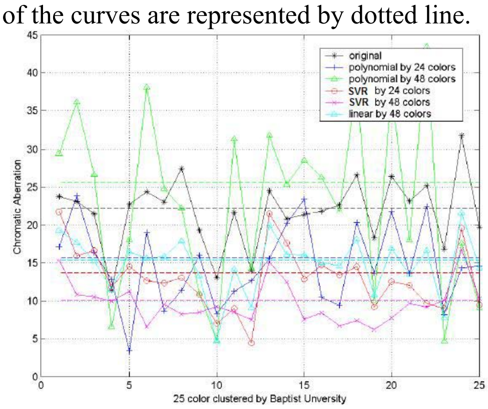
$$\hat{L}_{oth}^i = f_L(L_{oth}^i, a_{oth}^i, b_{oth}^i) \qquad (16)$$

$$\hat{a}_{oth}^i = f_a(L_{oth}^i, a_{oth}^i, b_{oth}^i) \qquad (17)$$

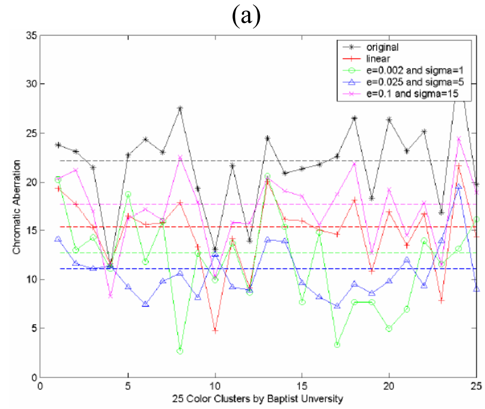
$$\hat{b}_{oth}^i = f_b(L_{oth}^i, a_{oth}^i, b_{oth}^i). \qquad (18)$$

7. Experimental Results

This section presents examples for practical color calibration applications on tongue images. The comparison analysis of different methods is shown in Figure 4(a). In this diagram, chromatic aberration curves of color cells clustered by [7] are marked as different color and mean values of the curves are represented by dotted line.



(a)



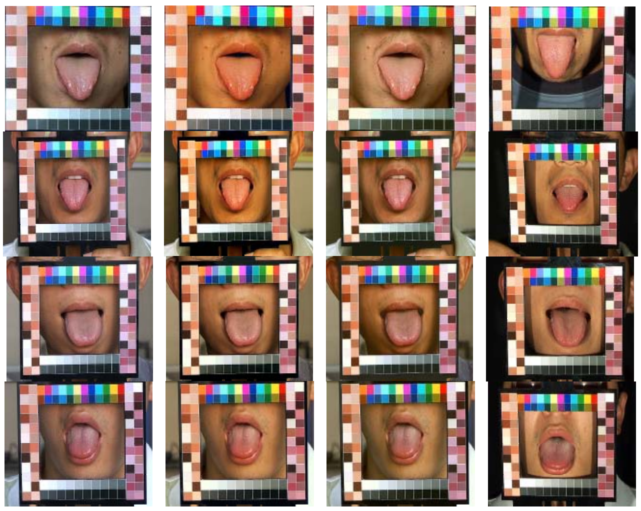
(b)

Figure 4. Comparison of the calibration effect (a) is calibration effects with different methods and (b) is those of SVR based calibration with different parameters

Chromatic aberrations of these cells can describe the degree of chromatic similarity between calibrated image and the target image. Note that, SVR based methods have an overall better performance than polynomial method. Moreover, the calibration result of SVR based method utilizing both windows 24 color cells and color cells clustered by us is the best of all methods.

Furthermore, the optimization of the parameters of Polynomial regression and SVR based calibration methods are carried out. For polynomial regression, 17 combinations of polynomial terms are tested. The result indicates that the polynomial combination, with the terms set $\{1, X, Y, Z, XY, XZ, YZ, X^2, Y^2, Z^2\}$, is better than others. So, all the polynomial regressions in the following experiments of polynomial regression based calibration are using this combination form. For the SVR with Gaussian RBF kernel, each support vector contributes one local Gaussian function, centered at the corresponding data point. According to the SVR principle, the global basis function σ should be adjusted. Large σ will make the regression similar to linear regression. On the other hand, adjusting the values of ε can avoid over-fitting of regression and control the amount of support vectors. The different calibration results corresponding to different σ and ε value are shown in Figure 4(b). From the diagram, it can be seen that the calibration results with $\sigma = 5$ and $\varepsilon = 0.025$ is better than others.

Figure 5 presents some examples of different color calibration results with the above parameters. The mean of chromatic aberrations between cells of image calibrated by polynomial based method and those of standard image is 38.124, but it decreases to 11.404 when using the SVR based methods. Therefore, SVR based method with such parameters is proposed for tongue image color calibration.

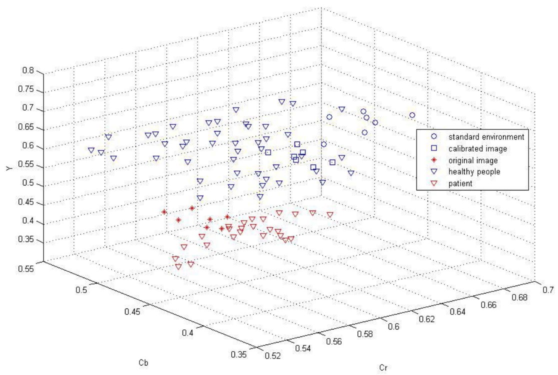


(a) (b) (c) (d)

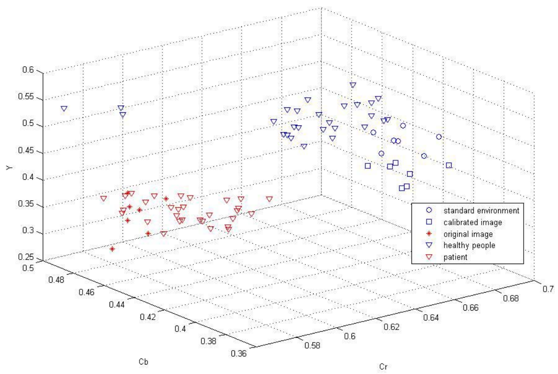
Figure 5. Examples of tongue image color calibration

Column (a) are the original tongue images before calibration, columns (b) and (c) are the calibrated image corresponding to Polynomial and SVR based model, and column (d) are the images captured under standard environment.

Finally, to provide an objective evaluation for the calibration methods, application test is carried out in a practical diagnosis process of a CATDS developed by Biocomputing Center, Harbin Institute of Technology (HIT). We combine 21 tongue images of 7 healthy people captured under standard, other lighting conditions and after calibration respectively into 84 tongue images retrieved from pathological tongue image database, and then input them to the CATDS for color classification. As shown in Figure 6, the original images captured under day-lighting condition are wrongly classified into disease (pancreatitis) class, while the images captured under standard environment and the calibrated images are classified into healthy class. In addition, we apply the proposed calibration method to the calibration of tongue images captured from 268 healthy students in HIT and 132 patients in PLA 211 hospital (under standard environment and nature lighting) and finally get 91.25% effectivity (chromatic aberration is less than 15).



(a)



(b)

Figure 6. Color classification result of CATDS

(a) classification based on tongue fur, while (b) classification based on tongue substance

8. Conclusions

To circumvent the color distortion problems and image interchangeable problems in tongue image acquisition, we propose a novel SVR based color calibration methods by comparing difference calibration models. Moreover, a new kind of colorchecker suitable for tongue color calibration is also produced by color clustering of tongue images in our database. Experiments show that the SVR based calibration method, cooperating with the proposed colorchecker provides better overall performance than that of Polynomial based methods. Furthermore, an optimized parameter set of SVR, as well as some evaluation criterions for acquisition environment and calibration effect are suggested in the paper. Finally, practical test on CATDS proved that the proposed method is consistently feasible and reliable for tongue diagnosis applications.

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