COLOR CALIBRATION MODEL OF SKIN LESION IMAGES FOR COMPUTER-AIDED DIAGNOSTIC

Leszek A. Nowak, Marcin P. Pawłowski, Katarzyna Grzesiak-Kopeć, Maciej J. Ogorzałek

Department of Information Technologies at Faculty of Physics, Astronomy and Applied Computer Science, Jagiellonian University, Reymonta 4, 30-059 Kraków, Poland
leszek.nowak@uj.edu.pl, marcin.pawlowski@uj.edu.pl, katarzyna.grzesiak-kopec@uj.edu.pl, maciej.ogorzalek@uj.edu.pl

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Abstract

Computer-aided diagnostic is developing rapidly and is being introduced in multiple fields of medicine. One of those fields is dermatology where various types of equipment are used for image acquisition. Those images can be processed in order to assist diagnostic by giving comparative examples, initial image enhancement or automated evaluation. In our research we concentrate on creation of computer-aided methods for skin lesion diagnostics, especially Malignant Melanoma screening based on ABCD evaluation rule [1]. While preparing these methods a number of issues appeared over and over again. The problems are due to the fact that we work with datasets that were obtained from equipment with different characteristics. The methods giving excellent results on one set of images may not perform as well on the others. Solving this problem usually requires manual fine-tuning of a set of parameters. In this paper we introduce a method of automated image adjustment based on color calibration model for calculating the Total Dermoscopy Score (TDS) of the ABCD rule. First we describe the general problem of skin lesion diagnostic and our motivation for the research. Next we will introduce the idea behind the method and its implementation. Finally the practical usage will be shown and discussed.

1 Introduction

There has been an explosion of skin cancer cases diagnosed in the last decade. Yearly increase of diagnosed new cases is around 20%. The location on the Earth determines skin cancer incidence. Southern Europe, with 6-10 per 100'000, has the lowest number of new cases. The highest incidence is noted in Australia with 50-60 per 100'000. Medical doctors are using various imaging methods on per-diagnosis basis. Dermoscopy is the most common non-invasive approach in skin cancer diagnostics. This procedure requires the doctor to examine magnified images of skin lesion to determine the diagnosis. Statistical study shows that this method is highly dependent on medical practitioner skills (see Table 1 for reference). [2]

Physician	Sensitivity	Specificity
Experts	90%	59%
Dermatologists	81%	60%
Trainees	85%	36%
General practitioners	62%	63%

The existence of several standardized approaches for analysis and diagnosis of cutaneous lesions [3] suggests that computer aided diagnostic is possible. The ABCD rule is one of the most popular methods which allows for calculation of TDS coefficient (Total Dermoscopy Score)

$$TDS = A * 1{,}3 + B * 0{,}1 + C * 0{,}5 + D * 0{,}5 \qquad (1)$$

Where the A, B, C and D values correspond to different features of the lesion:
A – asymmetry,
B – border,
C – colors (red, blue-gray, brown, black, white),
D – dermoscopic structures

Last decade gave us many specific approaches for calculating A, B, C values which have been successfully integrated in software packages [4, 5]. Computer aided calculation of D parameter is very difficult because the dermoscopic structures are hard to define, detect and assess. They can be distinguished as globular, cobblestone, lacunar, homogeneous, parallel, starburst and many other patterns.

Improvement of diagnosis process and assistance in correct decision making is in our belief achievable thanks to the digital image processing, feature extraction and classification methods.

In general the image processing is based on a set of images coming from a single source. This means that methods used on different set of data might require manual modifications. To overcome this problem, preprocessing or data normalization is used, e.g. histogram equalization, [6] or contrast enhancement. Unfortunately in computer aided skin lesion evaluation process, standard normalization is not always possible or it is simply unwise, as color variation (see Figure 1) is one of the most important diagnostic aspects. Because of the importance of colorimetric information, image processing methods need to be as insensitive to unwanted color deviations as possible.

Table 1. Performance figures for medical doctors.

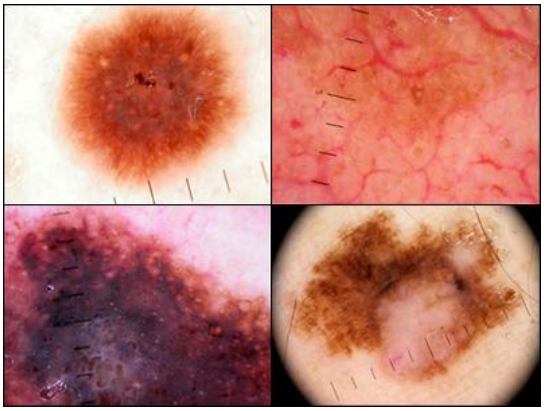

Figure 1. Examples of different skin lesion images that represent color variations that can usually be found during clinical evaluation process.

2 Motivation and problem description

While developing a semi-smart agent system designed to detect pigmented network (one of the dermoscopic structures used in ABCD scale) [7], the goal was to create system that was resistant to color intensity variations. Our system performed well the task on the group of images used in development but it performed unsatisfactory on new dataset. Further research revealed that development of the agent system was done on set of images that are similar in terms of color variance but differ in color intensity. As primary solution we have used dataset with images characterized by significant hue shifts.

We found ourselves in situation where newly developed system required by-hand adjustments to work properly on dataset that differ from the development dataset. Trying to solve the problem, common methods of normalization was applied, e.g. histogram equalization, background subtraction, contrast enhancement. Unfortunately these methods influence the image in undesired manner and/or require manual processing. This is not acceptable as our aim is to create automated system that process images and adapt accordingly to the image processed. To achieve this goal a lesion color model was created which allows automatic adjustment of image processing methods and image color calibration. Next we explain how images can be calibrated to match different color characteristics.

3 Methods for model calculation

For melanocytic image processing problem, we have noticed that the dataset we normally use in our research can be divided into four different groups of images that differ significantly in colorimetric characteristics (see Figure 2. for reference). These groups of images can be named:

- "standard" (later called "base model"),
- "white" (over-exposed images),
- "pink" (incorrect red color balance),
- "blue" (incorrect blue color balance)

Image examples for each group can be found on website[1]

[1] http://www.doit.fais.uj.edu.pl/color-calibration-model

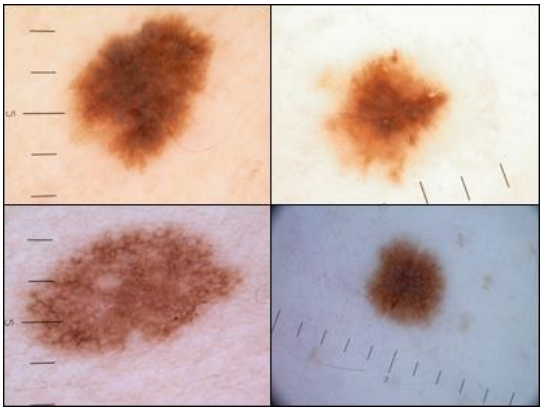

Figure 2. Four image groups found in dataset used for solving color model calibration problem. Those groups are: standard model (top left), consist of 37 images, 30 images in white group (top right), 13 images in pink group (bottom left), and 32 images in blue group (bottom right)

As mentioned in the earlier section, the image processing approach has been developed using images qualified here as "standard" and is used to calculate the base model. Base model calculated for one image is illustrated in Figure 3, and it is a 4-dimensional representation of image color incidence.

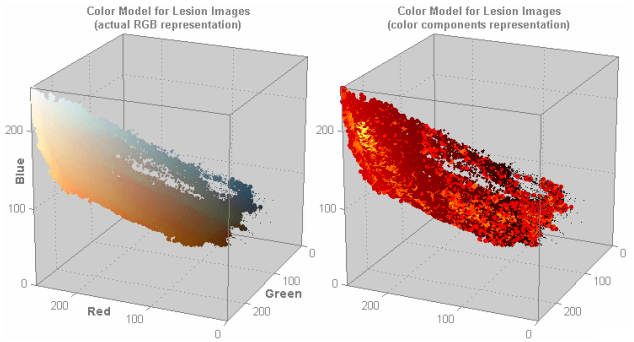

Figure 3. The image illustrates single image model for one of the images composing the base model. The scatterplot itself is a volumetric representation of every RGB component variation found on image. On the left side the actual color for RGB representation is visible. On the right volumetric information is shown using black to white heat map (brighter color means more frequent is the RGB variation).

We define an image as a set of colored pixels in the following way:

$$I = \{(p, c): p \in R^2, c = (c_r, c_g, c_b) \in < 0{,}255 >^3\},$$

where p denotes a pixel and c denotes its color in the RGB color model. For each color that appears in the given image I, we calculate the total number of its occurrences:

$$t_c^I = \#\{(p, c') \in I: c = c'\}$$

Then we calculate the total number of occurrence of each color present in any image from the given image dataset S:

$$T_c^S = \sum_{I \in S} t_c^I$$

Having defined the basic concepts we may finally present a color calibration model (cc model) for an image I:

$$m_I = \{(c, t_c^I): t_c^I > 0\}$$

A cc model is a set of pairs, where the first element is a color and the second is the number of its total occurrences in the given image I. Taking into account the whole set of images S we propose to define a base cc model:

$$M_S = \{(c, T_c^S): T_c^S > 0\}$$

We have made a number of approaches to extract the most important information from the base cc model. The most promising one is to calculate 4D histogram of local maxima. Such histogram is shown on Figure 4. Every point on the scatterplot represents one local maximum, its corresponding color and incidence (represented by the heat map and size of the marker).

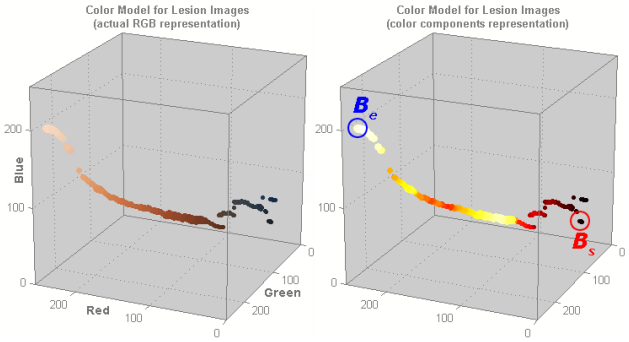

Figure 4. The figure illustrates the 4D histogram. The histogram consists of points located in RGB color space (actual color representation is presented on the left image). Each point on the plot represents maximal neighborhood value (one for each Red channel step). Points B_s and point B_e indicate the points used in calibration process.

In order to define the local maxima histogram H, first we have to introduce the notion of the color neighborhood:

$$n_c = \{c' \in <0,255>^3 : \| c - c' \| \leq 5\}$$

where ||c-c'|| states for an Euclidean distance between two colors, namely c and c'. So the neighborhood is a 5 pixel radius sphere with the color c in the middle. The neighborhood can be calculated along any color component (Red, Green or Blue) in the following way:

$$n_c^r = \{c' \in \{c_r\} \times <0,255> \times <0,255> : \| c - c' \| \leq 5\}$$
$$n_c^g = \{c' \in <0,255> \times \{c_g\} \times <0,255> : \| c - c' \| \leq 5\}$$
$$n_c^b = \{c' \in <0,255> \times <0,255> \times \{c_b\} : \| c - c' \| \leq 5\}$$

Using any of them gives no visual differences on the processed images. Let us assume that we select Red for the further consideration.

To calculate the local maxima histogram, we average the total number of occurrence of color c in the set of images S along the Red component:

$$\tilde{T}_{c_r}^S = \sum_{c' \in n_c^r} \frac{T_{c'}^S}{1 + \| c' \|}$$

And finally we may calculate the local maxima histogram:

$$H_r^S = \{(c, t_{c_r}^S): t_{c_r}^S = \max_{c' \in n_c^g \cup n_c^b} T_{c'}^S\}$$

4 Results

After creating the 4D histogram we can choose a method of calibration. In this paper we focus on using the model to calibrate images to match colorimetric properties of the base model. To do this we need to calculate 4D histogram for the processed image or set of images. This is done by using the same method as the one used while calculating the base model.

Resulting model (see Figure 5.) give us rough knowledge about the characteristics of the dataset that is to be calibrated. As an example we present steps of the algorithm and results for the blue dataset. The blue dataset is chosen because of its strongest deviation from the base model.

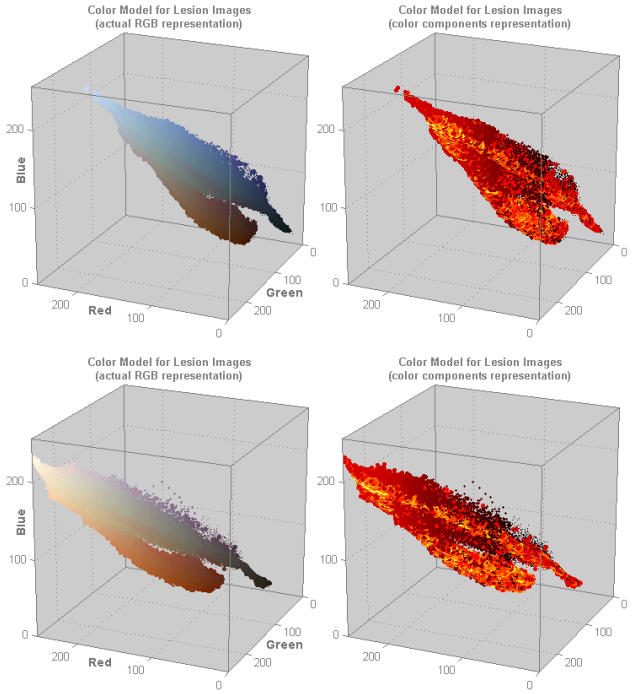

Figure 5. Image illustrates general color model for one of the images from the blue group. Images on the left show set of points corresponding to actual color of points in the image. On the right volumetric information about the same points is present (brighter color mean higher value). Top row is color model before calibration. Bottom row is color model after calibration.

It may be difficult to see the spatial distribution on given figure, although it is possible to observe that in the blue output model, large portion of points is shifted to higher values in red channel. This shift results in characteristic blue color of the images and influence method used in detection of one of the dermoscopic structures (blue-white veil). Viewing Figure 5 a comparison can be made between models representing blue shift occurrence and already calibrated model. Exact model visualization can be found on our department website[2].

Next step is to calculate the 4D histogram of the dataset that is calibrated. Using the same method as this is done

[2] http://www.doit.fais.uj.edu.pl/color-calibration-model

for base model. The resulting histogram is directly used for calibration purpose.

The calibration is based on finding the proper transformation of 4D histogram of dataset under calibration so that it will better match the 4D histogram of base model. Next we describe an example of performed transformation applied on 4D histogram.

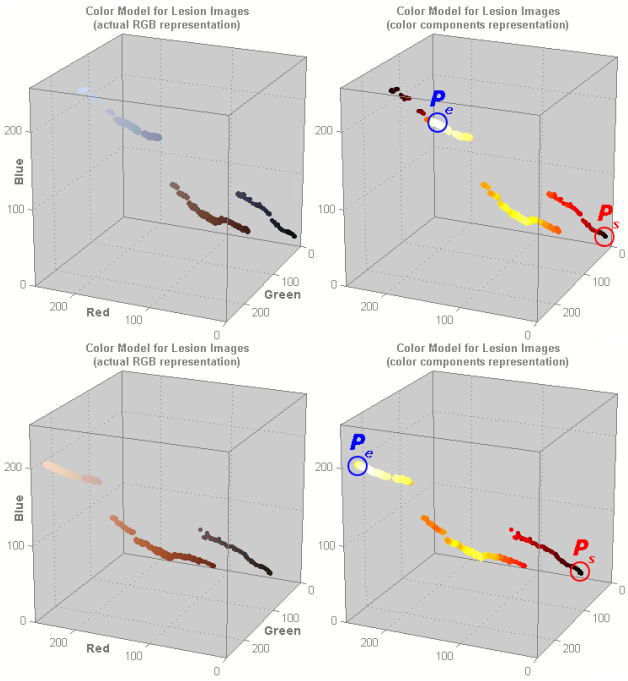

Figure 6. Image illustrates 4D histogram for one image from the blue group. Points P_s and point P_e indicate the points used in calibration process. Top row image illustrate 4D histogram before calibration, and bottom image illustrate 4D histogram after calibration.

Finding the proper transformation involves calculating at least two points of interest that correspond to high density regions found on the model. Those high density regions can be identified on the right side of the Figure 6, where incidence information is visible (brighter color indicate higher incidence). One of the points of interest (is be called: P_s) is a point of the 4D histogram that corresponds on the darkest colors visible on the images. These colors may indicate: hairs, vignetting, or high concentration of melanin in the skin. This P_s should be ideally in coordinates (0,0,0) in both the base model and model that is calibrated. In most situations this is not the case. Second point of interest (is be called: P_s) indicate position of highest occurrence of 4D histogram. This will set P_e to the coordinates pointing on R,G,B, channel configuration that is most often present on the model.

Having calculated P_s and P_e allow us to manipulate the special distribution of color model of processed dataset using linear transformation.

To calibrate dataset it is necessary to calculate points of interest for base model as well. We will call them B_s representing minimal (closest to (0,0,0) of R,G,B configuration) incidence found in model, and B_e representing maximal incidence.

The process of calibration begins with alignment of color channels of calibrated dataset, so that it matches the color channel of the base dataset. To do this we need to shift every color channels. The channel shift rate is calculated according to the equation:

$$shift^r = {B_s}^r - {P_s}^r$$

The shift is applied to every point of the processed image so that if we would calculate 4D histogram again, point P_s would closely match point B_s of the base model. Similar transformation need to be made for points P_e, and B_e to align. This is done by multiplying every point of the image by scale factor that is calculated by using equation:

$$scale^r = \frac{{P_s}^r}{{B_s}^r}$$

Results of the complete process are illustrated throughout Figures 5-6 as the bottom line of each image pair. Final output of applied method is presented on Figure 7 as three pairs of before-after images.

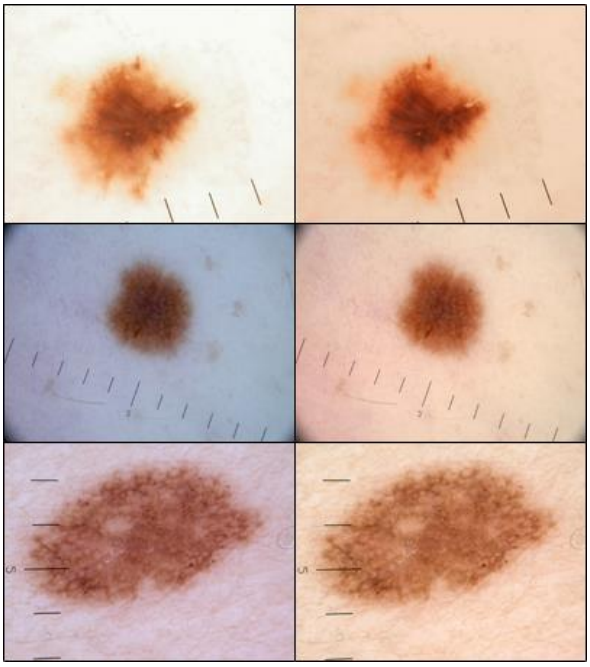

Figure 7. Image illustrates example calibration results for each group image. From top: white, blue, and pink.

5 Conclusion

We have presented here a color calibration model of images using only 2 points of interest, although more points may be used to calibrate images in regard of pigmentation colors that are defined and searched for in dermoscopic images. Those colors are specific to differential structures, and we wish to apply the model to extract only certain colors of interest and automatically adjust methods used in computer-aided diagnostics process.

Furthermore it is important to note that base model can consist of only one image and successfully serve as a model for future calibration, although the selected image should be as specific for the group as possible.
Computational complexity is linear to the size of processed images and their number.

Proposed method of calibration performed significantly better than expected, although further testing is required using more differentiated datasets. Thorough verification need to be performed if calibrated images does not give any artifacts while being processed with specialized image processing methods.

Acknowledgments

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