COLOR CONVERTING OF ENDOSCOPIC IMAGES USING DECOMPOSITION THEORY AND PRINCIPAL COMPONENT ANALYSIS

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ABSTRACT

Endoscopic color imaging technology has been a great improvement to assist clinicians in making better decisions since the initial introduction. In this study, a novel combined method, including quadratic objective functions for the dichromatic model by Krebs et al. and Wyszecki`s spectral decomposition theory and the well-known principal component analysis technique is employed. New algorithm method working for color space converting of a conventional endoscopic color image, as a target image, with a Narrow Band Image (NBI), as a source image.

The images of the target and the source are captured under known illuminant/sensor/filters combinations, and matrix Q of the decomposition theory is computed for such combinations. The intrinsic images which are extracted from the Krebs technique are multiplied by the matrix Q to obtain their corresponding fundamental stimuli. Subsequently, the principal component analysis technique was applied to the obtained fundamental stimuli in order to prepare the eigenvectors of the target and the source. Finally, the first three eigenvectors of each matrix were then considered as the converting mapping matrix. The results precisely seem that the color gamut of the converted target image gets closer to the NBI image color gamut.

KEYWORDS

Color Converting, Endoscopic Imaging, Dichromatic Model, Principal Component Analysis, Decomposition Theory.

1. INTRODUCTION

Since the time that endoscopic imaging technology of human internal organs was introduced, the researchers of color image processing have been looking for creating methods to improve medical diagnosis[19,20]. The new methods were expected to improve the visualization of lesions and problems of the tissue under visual assessment. For instance, endoscopic images that are provided under narrow-band light sources i.e., Narrow-Band Imaging (NBI), have been clinically proved to have a higher quality of medical diagnosis in spite of the fact that they do not show the colors similar to the conditions in which the tissue is imaged with white light[1,2]. Consequently, from this point of view, correct transfer of the tissue color during digital representation of the image does not necessarily have priority anymore, but instead as

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our purpose, we can devise methods to change the color space of the image to increase the quality in the visual assessment of endoscopic images.

The topic of the color change of an image is a valuable one that has useful applications in color image enhancement, color constancy, color gamut mapping, and color reproduction in space telescope images, artistic images, industrial images, etc. [3-6].

One of the techniques for color changing of an image is the ability to transfer the color space of a source image to a target image. There are various and interesting researches conducted in this area as well.

Saito et al. proposed a histogram matching method between two color gamuts, based on matching the minimum and maximum values of the source image to the corresponding values of the target image [7,8]. Likewise, Gorji Kandi et al. suggested a histogram rescaling between two color gamuts using Rosenfeld-Kak histogram matching based on matching the R, G, and B channels of the source image to the corresponding histograms of the target image [9]. Reinhard et al. attempted to match the means and variances between the target and the source image by converting RGB into Lαβ color space which is developed with Ruderman et al. Afterwards, they determined the means and standard deviations for any axis separately in Lαβ space and eventually converted the enhanced result back to RGB [10]. Chang et al. introduced a color category-based method by classifying each pixel as one of the basic categories. Then a convex hull was produced in Lαβ color space for each category of the pixel sets, and the color transformation was applied with each pair of the convex hull of the same category [11]. Paris et al. proposed the Local Laplacian Pyramid method to profit the edge-preserving decomposition for the desired level of detail manipulation [12].

Abadpour et al., who used the fuzzy principal component analysis-based clustering technique (FPCAC), developed an independent color space to minimize color correlation by finding two sets of membership maps as a result of the clustering concerning the cluster parameters [13]. By contrast, a survey review by Dhanve et al. shows that the majority of methods would be producing insufficient similar color distortion and grain effect [14].

This study proposes a new method of converting color space from aNBI image to a standard endoscopic image of internal organ. The purpose is to enhance such endoscopic images to provides a better visual assessment quality for the medical diagnoses.

2. METHOD AND RESULTS

2.1. Applying Dichromatic Model

The color appearance of human internal tissues is a consequence of color, gloss, and texture. In our approach, it is required to separate the shading factor and specularity from intrinsic image for each pixel. Among various techniques, we selected and applied the Krebs et al. technique based on the quadratic objective functions to estimate dichromatic model parameters from a single color image [15]. The dichromatic model was introduced by Shafer et al. in 1985[16]. This model represents an image as a linear combination of the photometric invariants:

$$I(u;\, n) = L(\lambda)(g(u)S(u;\, n) + k(u)) \qquad (1)$$

Where in equation (1), *I* is the input image, L is the illuminant multiplied by the sensor and filters sensitivity, g is the shading factor, k is the specularity, and S is the intrinsic image. Also, u and λ denoted the pixel location and the number of channels, respectively. Figure 1 and Figure2 show the dichromatic estimated S, g, and k of the source and target images. The source and the target are a typical example of NBI and conventional endoscopic images.

2.2. Applying Matrix Q

We assumed the source and the target images are captured under known illuminant/sensor/filters combinations, and then matrix Q of the decomposition theory is computed for such combination. Decomposition theory by Cohen and Kappauf was introduced and employed as an orthogonal projector, and it was attained from the Wyszecki`s spectral decomposition theory. Based on the Wyszecki hypothesis, In a series of articles, Cohen and Kappauf formalized a mathematical technique for decomposing the intrinsic image S(u; n) as a stimuli, into its fundamental stimuli, S_{FCS} through a framework of orthogonal projectors using linear algebra[17]. Fundamental stimuli is intrinsically associated with the color values shared to all possible metamers ever to be encountered [21].

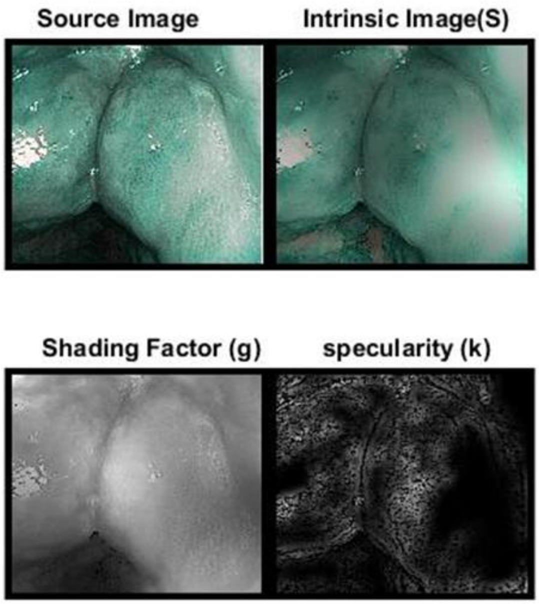

Figure 1. The Source image[2] and its intrinsic image (S), shading factor(g), and secularity(k) using the dichromatic model estimation.

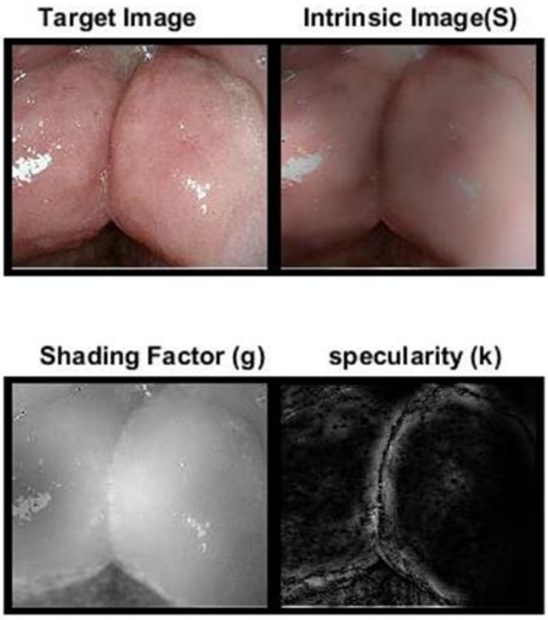

Figure 2. The Target image[2] and its intrinsic image (S), shading factor(g), and specularity(k) using the dichromatic model estimation.

$$S = L'N \qquad (2)$$

By uniformly sampling for each pixel in equation (2) , L is a p×3 matrix, provides a mapping from usually large p-dimensional intervals of spectral reflectance, N into only three-dimensional stimuli, S. Because of this tense dimensionality reduction, there are theoretically exist many different spectral reflectance Ni (i = 1,...,m) which all can represent the same stimuli, S.

$$L'N_i = S \qquad (3)$$

Premultiplying any 3×1 dimensional vectors of S by the p×3 matrix, L $(L' L)^{-1}$produce a p×1 dimensional vector of SFCS [18].

$$L\ (L'\ L)^{-1}\ L'\ N_i = L\ (L'\ L)^{-1}\ S = S_{FCS} \qquad (4)$$

The equality L $(L' L)^{-1}$ S = SFCS lets compute the fundamental stimuli, SFCS from stimuli, S for each pixels. It would be called matrix Q.

$$\text{Matrix } Q = L\ (L'\ L)^{-1} \qquad (5)$$

Figure 3shows the fundamental stimuli, SFCS for each pixels of the source and the target images by computing of the corresponding L for illuminant/sensor/filters combinations which are employed to calculatetheirown matrixQ.

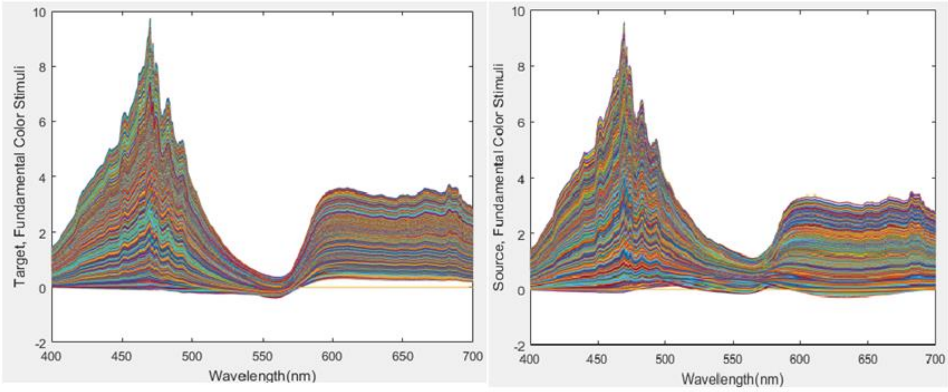

Figure 3. The fundamental stimuli(S_{FCS}) of pixels: the source image(left), the target image(right).

2.3. Applying Principal Component Analysis

Then, we extructed eigenvectors and eigenvalues of the S_{FCS} matrix of the source and the target by the well-known principal component analysis, PCA technique. Extracted eigenvectors sorted according to their corresponding eigenvalue importance. Computing cumulative index of diagonal eigenvalue matrix of the source and the target shows the first three eigenvectors, prepares enough information to fully recover the co-variance matrix of the source and the target`s S_{FCS}. Then we compute the specifically weighted coefficient (α) of the PCA technique that needs to recover each S_{FCS} belonging to the source and the target.

Consequently, color converting would be prepared by estimating new $\hat{S}_{FCS}$ values of the target. $\hat{S}_{FCS}$ of the target is easily estimated with multiplying the first three eigenvectors, 3PC of the source`s S_{FCS}, by the specifically weighted coefficients of the target.

$$Estimated\hat{S}_{FCS} = \alpha_{target} \times 3Pc_{source} \qquad (6)$$

The last step is continued by changing the estimated $\hat{S}_{FCS}$ to estimated $\hat{S}$ for each pixels of the target in aid of L and finalized the method by recombining $\hat{S}$ with its corresponding g and k. This gives new values converted target, $\check{I}$ for each pixels of the target image. Figure 4 shows flowchart of the proposed color converting method using dichromatic model, decomposition theory and principal component analysis.

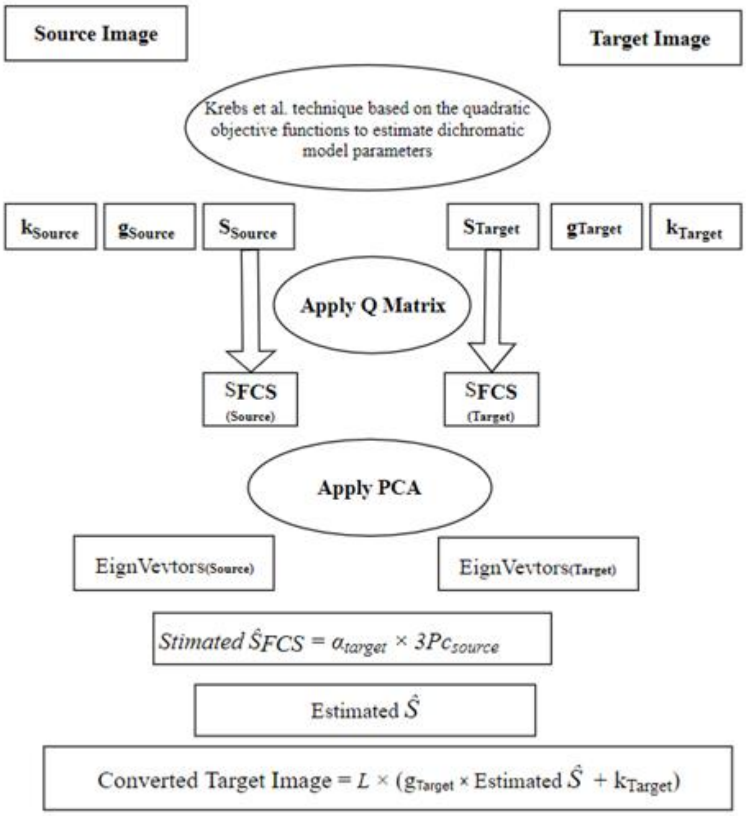

Figure 4. Flow chart of the proposed color converting using decomposition theory and principal component analysis.

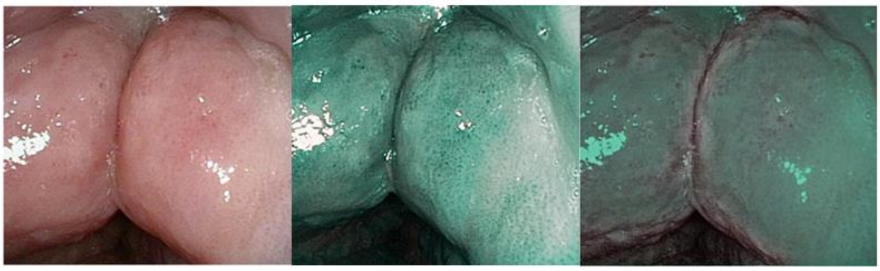

Figure 5. The target image(left), the source image(middle), the converted target image(right).

Figure 5 shows the result of the converted color space of the source image to the new target image in comparison with the original target image. It can be seen that the suggested method can provide the possibility to convert the color spaces between images. For more clarification, the color gamut of the source, target, and converted target images are shown in Figure 6. As indicated, the color gamut of the converted target image gets closer to the NBI image color space after applying the suggested color converting technique.

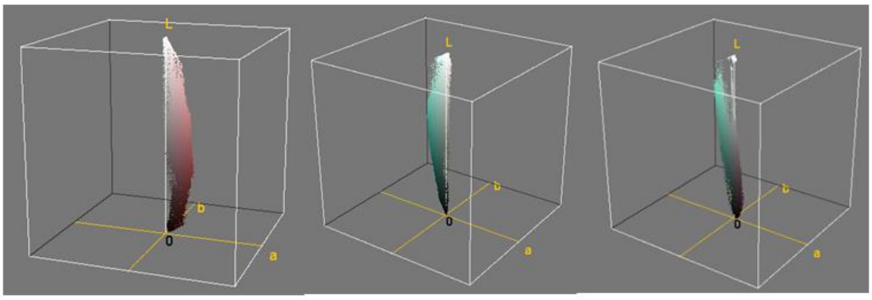

Figure 6. The CIELAB color gamuts of : the target image(left), the source image(middel) and the converted target image(right).

3. Conclusion

A hands-on novel technique was introduced to convert the color gamut atmosphere of a narrowband image into the conventional target image. This new combined technique would be valuable in the field of medical endoscopic color image enhancement and clinical diagnoses.

Firstly, the quadratic objective functions for the dichromatic model by Krebs et al. applied to estimate optical parameters such as intrinsic image, shading, and specularity from the source image (narrowband endoscopic color image) and the target image (conventional endoscopic color image).

Secondly, the decomposition theory was introduced by Cohen and Kappauf as an orthogonal projector to the Wyszecki`s spectral decomposition theory, employed to obtain the fundamental stimuli of the intrinsic image belonging to the target and the source images.
Finally, by using the principal component analysis classic technique, the first three eigenvectors of the fundamental stimuli of the target image were taken and replaced by eigenvectors of the fundamental stimuli of the source image.

The resulting image and the color gamut's were showed that this new algorithm could be feasibly applied for color space converting between color images, such as Narrow Band Images(NBI), into the conventional endoscopic color images.

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