Image Fusion in Spectral Electronic Endoscope

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Abstract

In this paper, we propose the automatic image fusion technique to obtain significant information from each spectral image component and to combine three the components in an RGB image. The proposed fusion method is intended for use with a new electronic endoscope which is significantly more efficient in diagnosing various types of diseases than conventional electronic endoscopes using RGB information. The purpose of the proposed method is to provide improved reproductions of endoscope images, especially blood vessel structures, that agree with human vision and provide clinicians with more information. The conducted experiment confirms method's feasibility and shows that the proposed method is superior to the method using Optimum Index Factor.

Introduction

Recently, a new electronic endoscope was developed to record and reproduce arbitrary spectral images of the mucous membrane such as the gullet, colon and stomach. The developed endoscope is significantly more efficient in diagnosing various kinds of diseases than conventional electronic endoscopes using RGB color information. The introduction of spectral endoscope requires management of endoscope images by using the image database that provides doctors with relevant information preventing possible surgical intervention. The direct participation of doctors in the analysis of spectral endoscope images is not desirable because it is difficult for a human to integrate information even from the one spectral image with several dozens of components. For example, if we use an n component image where $n = 61$ and need to implement RGB fusion $k = 3$ then there are $n!/(k!(n-k)!) = 35990$ possible combinations. Therefore, automatic image fusion is required.[4]

Spectral image fusion techniques are grouped into two classes: statistical (numerical) methods and color related methods [8]. Numerical methods include principal component analysis, multiresolution approaches based on wavelets, methods based on arithmetical operations between spectral components and methods using component correlation and filters [8]. The color related approaches include component selection for RGB (IHS) color system, integration of spectral data in RGB (or IHS) color space and substitution of one or three color components with an image from another source [8]. The fusion takes place on three levels: pixel, feature and decision [6, 8]. In this paper, we consider a novel method, which uses spectral component selection algorithm and is related to RGB color fusion.

In the overview of definitions of data fusion only one definition addresses quality: “fusion refers to the combination of a group of sensors with the objective of reproducing a single signal of greater quality and reliability” [11]. There are many quality measures for image fusion including statistics (Fisher distance, information entropy and mutual information) [2, 3, 9] and objective measures [7, 13]. Apart from the mutual information measure, statistic measures compute either a separation measure between the target and its background or the image complexity. The most widely used mutual information and objective measures estimate what information is transferred from the input images to the fused image. These measures are not suitable in our case as we select spectral components to implement RGB fusion. In our study we show that an image quality measure based on observer perceptions and oriented for medicine should be used in the component selection task. We cannot also use the conventional image quality measures like SSIM [12] because they require a reference image and are not intended for color images. Therefore we shell directly estimate quality of the fused images. We also present two main objectives of endoscope image fusion in order to increase spatial resolution and to enhance certain features not visible in either of the single spectral components alone.

In this paper, we describe automatic image fusion to obtain significant information from each of the image components (band) and to combine three of them in an RGB color image. The task of image fusion is to provide enhanced sharpness and color of an image structure (blood vessel structures and areas degraded by diseases) that agree with human vision and provide the clinicians with more details.

Image Fusion Based on Image Quality

The purpose of this study is to develop a component selection and fusion automatically based on relevant observer quality preferences and related to observer perceptions and physical image parameters. Our task is to select a combination of three components from a set of spectral components (a 61 component image) and use them in RGB fusion. In this study we use an estimation of image quality directly due to the lack of a relevant reference image. An original color image cannot be used as a reference because the quality of a synthetic image can be both better and worse in comparison to an original image. However, an approach with a reference image is found to be useful to correct a final result and to reduce the noise level. In this study we will follow the guidelines presented in the image quality circle introduced in [1]. The image quality circle includes the following: observer quality preference, observer perceptions, physical image parameters, image quality model, visual algorithm, system model and technology variables.

Observer image quality preference. Observer image quality preference is based on an overall image quality rating by the observer and based on a numerical scale, for example 1 to 10.

Observer perceptions. Observer perceptions include the most important image attributes. In photography, for example, they are graininess, sharpness, lightness reproduction-ness and hue-chroma reproduction-ness [1]. The quality of the endoscope images considered here relates to medical diagnostics made by doctors. Therefore, it is important to formulate a set of perceptions a priori if any relevant information is available. We recognize that this is a very initial, restricted and not fully defined set. However, using the first experiments where doctors provided component selections [4], we conclude that the most important perception factor in endoscope image fusion is sharpness. This coincides with the conventional viewpoint that the most important factor for fusion is how well the fusion technique emphasizes the local structure of an image that is an edge image [7]. However, while the role of sharpness of endoscope images corresponds to common knowledge, the role of color is less clear in the doctors' selection. In many fused images manually made by doctors, color is presented very scarcely. We assume that the doctors simply omitted the most interesting component combinations due to a huge amount of combinations needed for testing. In this study, we will show how by using a color selection technique we can discover image structures which cannot be reproduced with any other parameters or with conventional techniques such as pixel and region fusion. Thus, we consider colorfulness to be the second important factor in endoscope image fusion. This study explicitly involves computation of the physical parameters defining the sharpness and colorfulness and incorporates noiseless at the postprocessing stage.

Physical parameters. Physical parameters are the quantitative functions and parameters used to define image quality [1]. In our study, we specified two most important perception factors: sharpness and colorfulness. Therefore, we define two physical parameters, Fourier spectra and chromaticities, which relate to human perception factors such as hue and saturation.

Technology variables. Technology variables are the system parameters that the developer of the imaging system uses to change image quality [1]. In the imaging system considered here, that is a spectral electronic endoscope, such basic variables are the spectral estimating matrix converting the original RGB image into a spectral image and the matrix selecting three components for simulating a synthetic RGB image. The first stage we call component synthesis and the second stage we call component selection.

Visual algorithm. The algorithm is used to compute a value of perceptions (in our case sharpness and colorfulness) from a physical image parameter [1]. We consider sharpness that relates to the spatial frequency and colorfulness related to the chromaticity scope. Let us assume that we selected three components with different indices from a 61 component set representing the synthetic spectral image and ordered them according to the correspondent wavelength so that the component R, G and B are taken at the long, medium and short wavelength, respectively. In the preprocessing stage we scale the component pixel values as follows:

$$R \leftarrow (R - R_{\min})/(R_{\max} - R_{\min}), \qquad (1)$$

where $\leftarrow$ means a substitution. Similar scaling is used for G and B components. We adopt the system presented by intensity $I = R + G + B$ and chromaticities $r = R/(R + G + B)$ and $g = G/(R + G + B)$ incorporating hue and saturation information and robust to illumination change.

First, we consider sharpness. We propose to define sharpness by the relative frequency of two-dimensional Fourier spectrum of the intensity component I. The relative frequency F_r is computed as follows:

$$F_r = (F_r(u)^2 + F_r(v)^2)^{1/2}, \qquad (2)$$

where $F_r(u)$ and $F_r(v)$ are taken along horizontal and vertical coordinates of a two-dimensional Fourier spectrum. If an image size is $M \times N$ then the relative frequency for horizontal coordinate taken at $v = 0$ is as follows:

$$F_r(u) = |F(u)|_{\max}^{-1} \sum_{u=0}^{M-1} |F(u)| \quad . \qquad (3)$$

Geometrically, the relative frequency is equal to the width of the rectangle with a unit height and an area equal to the area under the enveloping frequency curve, that is the Area Under Curve (AUC), of the Fourier spectrum scaled by $|F(u)|_{\max}^{-1}$. The larger value of the relative frequency is the better image sharpness. This is an efficient measure that gives a set of advantages. This approach is computationally simple and does not require estimating the highest frequency of an image because the AUC incorporates information about the spectrum width. In addition, this measure works in the horizontal and vertical dimensions of the spectra and, thus, roughly approximates the anisotropic MTF of the human eye described in [5]. The drawback of this measure is that it is sensitive to noise because noise expands the spectrum. Usually the noisy components are presented in a short wavelength subrange. To reduce noise influence we have to replace these components by selecting them from the subset of components with the less noise level.

We determine colorfulness using the chromaticity images r and g. First, we compute a two-dimensional chromaticity histogram $hist\,(r, g)$. Next, we define colorfulness by relative chromaticity scope. Chromaticity scope is an area S occupied by the chromaticity histogram of the RGB image in a chromaticity diagram. The histogram values are taken when they exceed a threshold equal to two pixels. The relative chromaticity scope C_r is the chromaticity scope divided by the whole area of a chromaticity diagram. The larger the value of the relative chromaticity scope is, the better the colorfulness. If a number of bins along each coordinate of the chromaticity diagram is N, then the relative chromaticity scope is as follows:

$$C_r = 2S/((N+1)N). \qquad (4)$$

Thus, the relative frequency measure and the relative chromaticity scope measure are used to evaluate image sharpness and colorfulness. We compute two performance indices (sharpness and colorfulness, respectively) as follows:

$$PI_s = (F_r - F_{r\min})/(F_{r\max} - F_{r\min}), \qquad (5)$$
$$PI_c = (C_r - C_{r\min})/(C_{r\max} - C_{r\min}). \qquad (6)$$

The values of these performance indices are within the range [0, 1] and are convenient for combination of the performance indices to obtain the measure for overall image quality. Algorithm 1 shows the visual algorithm.

Algorithm 1. The visual algorithm.

Input: selected image $\mathbf{x} = |R, G, B|^T$.
Do:
1. Scale the input image using Eq. 1 and compute the intensity I and chromaticity images r and g.
2. Compute the relative frequency F_r using Eq. 2 and Eq. 3.
3. Compute the chromaticity histogram $hist(r, g)$ and the relative chromaticity scope C_r using Eq. 4.
4. Compute the performance indices PI_s and PI_c using Eq. 5 and Eq. 6, respectively.

Image quality model. Image quality models relate to customer perceptions and describe mathematically the trade-off the observer makes estimating image quality [1]. The image quality model described here and called the performance index PI is defined by a product of two terms PI_s and PI_c as follows:

$$PI = PI_s PI_c. \qquad (7)$$

We find a maximum PI by selecting three components of a spectral image. We consider that there is no a reason to make this model complicated by introducing other measures (contrast, lightness) at the expense of sharpness and colorfulness, which are the most important factors in image fusion. We also note that the applications based on Minkowski metrics and related metrics are successfully used in image quality model building [1]. However, in this case researchers face a problem in estimating the data dependant metric parameters. As a result, it is difficult to achieve a good generalization for a large set of endoscope images.

Fig. 1 shows the generic RGB color fusion scheme and the flow chart of the proposed method for component selection. We sequentially select three components from the given spectral image. The selected components are transformed into the intensity and chromaticity images. We use Fourier spectrum and a chromaticity histogram to compute the performance indices. Finally, only one component combination having a maximum performance index is used for RGB color fusion.

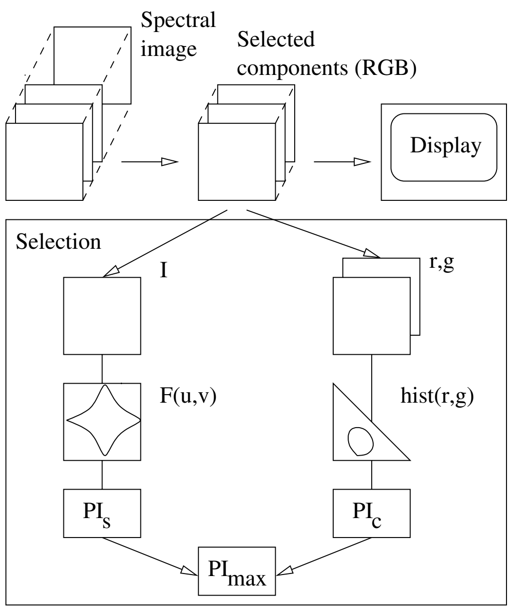

Figure 1. The generic RGB color fusion scheme and the flow chart of the proposed component selection method.

System models. System models are analytical models that predict the physical image parameters based on the technology variables [1]. Here we consider only the basic technological variables of a spectral endoscope. In the first stage, that is component synthesis, we convert the endoscope RGB image $\mathbf{z}$ into the 61 component spectral image $\mathbf{y} = \mathbf{A}\mathbf{z}$, where $\mathbf{A}$ is an estimating matrix with a size 61×3 [4]. The rows of $\mathbf{A}$ are technology variables. In the second stage, we use a selection matrix $\mathbf{W}$ to select three components used for RGB fusion $\mathbf{x}=\mathbf{W}\mathbf{y}$. The matrix $\mathbf{W}$ has a size 3×61. The three rows of $\mathbf{W}$ are technology variables. Each row of $\mathbf{W}$ consists of all zeros except one having a unit value. While the matrix $\mathbf{A}$ is defined at the spectral estimation stage, the matrix $\mathbf{W}$ design considered in our study directly relates to component selection. The maximum performance index and the direct search procedure determine the choice of unit elements in the rows of $\mathbf{W}$.

Noise Reduction

The noise problem is important for the proposed method since the components from the short wavelength range are frequently noisy. One of the measures used in our method and based on the relative frequency rely on the frequency spectrum width which can be increased due to noise influence. The basic idea for reducing the noise level is to reselect components intended for fusion taking them from the range with long wavelengths. Reducing noise we have to provide sharpness and colorfulness in the fused images. Therefore, we select the 200 component combinations which have the highest PI. Then, we measure the SSIM between an intensity image with a maximum PI and the intensity images of the selected combinations. The SSIM is an efficient approach for comparison the noisy image with a noiseless image [12]. Then, we select only 15 combinations from the 200 combinations. The selected combinations have the minimum SSIM values. In addition, the short wavelength component of each combination has the wavelength longer than the wavelength of the short wavelength component of an optimal (maximum PI) combination. Then, we select only one combination with a maximum PI_c from the 15 combinations. The last steps guarantee that the corrected image is still sharp and colorful. Finally, the image with the reduced noise level and the image without noise reduction are presented to the observer who has to select the best one.

Experiment

The five spectral endoscope images L003, L051, L040, L049 and L032 were analyzed using the proposed algorithm. The image size (horizontal and vertical) is 321×241 pixels and the spectral dimension is 61 components uniformly acquired at 5 nm in the range 400-700 nm. Except for the image L051, we are interested in improved reproduction of the blood vessel structure. For the image L051, we try to enhance the reproduction of an area degraded by diseases.

For comparative purposes, we use a statistic metric, that is the Optimum Index Factor OIF [8], which is maximized

$$OIF=\sum_{i=1}^{3}\sigma_i\left(\sum_{j=1}^{3}|\,cc_j\,|\right)^{-1} \quad , \quad (8)$$

where σ_i is the standard deviation of pixel values for component, cc_j is the correlation coefficient between each two of three components. Pixel values were normalized in the same way as for other metrics. To make comparison more interesting, the OIF is used only for components in the range 400–565 nm, where spectral components have better sharpness [10]. In this case, all possible combinations of components in the subrange are analyzed.

Table 1 shows the results for component selection using different metrics. First, we note that the maximum performance index related to sharpness is typically achieved by selecting components in the short wavelength subrange that confirms the results obtained in [10]. The maximum performance index related to colorfulness maximizes when components are selected from the whole wavelength range and stand out in a spectral domain. For the maximum performance index incorporating sharpness and colorfulness, the selected components belong roughly to the short wavelength subrange from 450 to 600 nm. These components stand out in a spectral domain in comparison to the sharpness metric. The OIF metric attempts to find components with long wavelengths which have a maximum variance. We build a Hinton diagram to see how the performance indices affect the entries of $\mathbf{W}$. Fig. 2 shows the results obtained for the endoscope image L003.

Finally, we conducted the experiment with subjective quality evaluation of the color and fused versions of endoscope images. 11 observers (9 males and 2 females) participated in the experiment. All observers had normal color vision and were inexperienced in making medical quality judgments. The test images were reproduced on an 17" LCD display. The light source had an illuminance of approximately 367 lux and the illumination values $x = 0.3707$ and $y = 0.3845$. The viewing distance was 50 cm and a non limited time was given for observation. The observers were asked to give their opinion about reproduction of the blood vessel structure using evaluation values from 1 to 10, where a higher number on the scale indicated better sharpness and better reproduction of vessels.

Fig. 3 shows image quality (mean values) for the test images made by observers. Fig. 4 shows the conventional color (endoscope) images and Fig. 5 shows the color images obtained by the proposed fusion method and corresponding to the conventional images. Fig. 3 shows that the proposed method outperforms conventional endoscope and the OIF based method. The proposed method improves image sharpness for all images. However, the color change caused by fusion produces the most interesting results shown in Fig. 5. Obviously, the fusion method utilizes the discriminative character of color: a vessel structure is separated better from the background and the thin and thick vessel structures acquire different colors. This makes it possible to observe vessel substructures as well. This effect is clearly observed in the images L003 and L032 which the observers ranked high. We see the bluish thick vessels in L003 and we see the reddish thin vessels and bluish thick vessels in L032. We note that the improvement of L051 with an area degraded by diseases (right-bottom corner) is not so dramatic, although image sharpness and contrast are better than in the conventional image.

Table 1. Selected components using different metrics. The values are wavelength, nm. The components for the images L040 and L032 are given after noise correction.

Metric	L003	L051	L040	L049	L032
PI_s	525 530 535	435 445 455	460 465 470	510 515 520	470 475 480
PI_c	470 535 660	470 540 650	455 530 650	460 525 670	450 530 650
PI	450 525 550	520 540 580	465 525 600	480 525 585	475 525 560
OIF	555 560 565	470 560 565	450 560 565	460 560 565	470 560 565

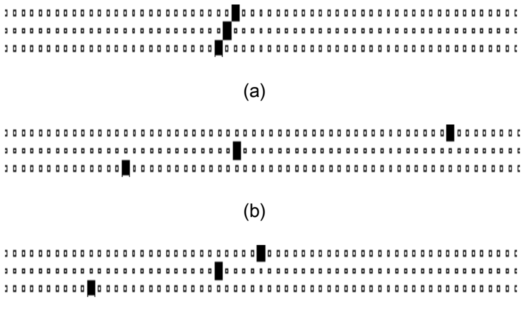

Figure 2. The Hinton diagrams of selection matrices. a) $\mathbf{W}$ for PI_s, b) $\mathbf{W}$ for PI_c and c) $\mathbf{W}$ for PI. The zero-valued elements are shown by small squares. The unit elements are shown by black squares. A horizontal position of elements corresponds to wavelength from 400 to 700 nm taken at 5 nm. The first, second and third row in each diagram define the selected R, G and B components, respectively.

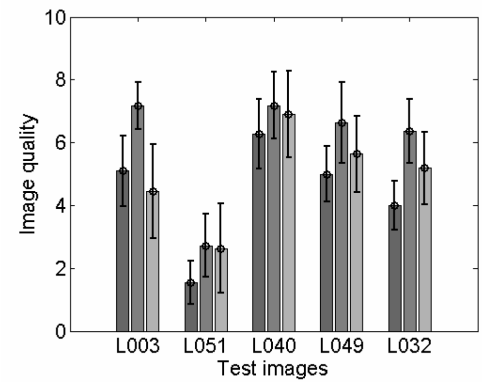

Figure 3. Image quality for the test images. For each test image the left, medium and right bars are given for a color image, an image fused by the proposed method and a fused image using the OIF, respectively. The error bars show the standard deviation values of observer estimates.

Conclusions

We proposed a novel method for image fusion in electronic endoscopes. We used the most important perception factors in medicine: sharpness and colorfulness to enhance the reproduction of blood vessel structures. The vessel structure in the fused images has better distinguishable colors than the conventional color images. Color information helps to separate the vessel structure from the background and to discover vessel substructures. The optimum between discriminative color and sharpness is achieved in the relatively short wavelength subrange.

Acknowledgments

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References

1. P. G. Engeldrum, Image Quality Modeling: Where Are We?, *Proc. PICS 1999*, Savannah, Arizona, IS&T, pp. 251-255, 1999.
2. E. F. Canga, S. G. Nikolov, C. N. Canagarajah, D. R. Bull, T. D. Dixon, J. M. Noyes and T. Troscianko, Characterization of Image Quality Metrics for Surveillance Applications over Bandlimited Channels, *Proc. The 8th International Conference on Information Fusion*, Vol. 1, ISBN: 0-7803-9286-8, pp. 483-490, 2005.
3. J. Liu, Q. Wang and Y. Shen, Comparison of Several Pixel-Level Image Fusion Schemes for Infrared and Visible Light Images, *Proc. Instrumentation and Measurement Technology Conference IMTC 2005*, Vol. 3, pp. 2024-2027, 2005.
4. Y. Miyake, T. Kouzu, S. Takeuchi, S. Yamataka, T. Nakaguchi and N. Tsumura, Development of New Electronic Endoscopes Using the Spectral Images of an Internal Organ, *Proc. the 13th Color Imaging Conference CIC 2005*, Scottsdale, Arizona, pp. 261-263., 2005.
5. Y. Miyake, Evaluation of Image Quality Based on Human Visual Characteristics, *Proc. the First International Workshop on Image Media Quality and its Applications,* Nagoya, Japan, pp. 10-14, 2005.
6. G. Piella, A General Framework for Multiresolution Image Fusion from Pixels to Regions, *J. Information Fusion*, Vol. 4., pp. 259-280, 2003.
7. G. Piella and H. A. Heijmans, A New Quality Metric for Image Fusion, *Proc. International Conference on Image Processing ICIP*, Vol. 3, pp. 173-176, 2003.
8. C. Pohl and J. L. Van Genderen, Multisensor Image Fusion in Remote Sensing: Concepts, Methods and Applications, *Int. J. Remote Sensing*, Vol. 19, No. 5, pp. 823-854, 1998.
9. F. Sadjadi, Comparative Image Fusion Analysis, *Proc. IEEE Conf. on Computer Vision and Pattern recognition CVPR 2005*, Vol. 3, pp. 8-8, June 2005.
10. N. Tsumura, T. Tanaka, H. Haneishi and Y. Miyake, Optimal Design of Mosaic Color Filters for the Improvement of Image Quality in Electronic Endoscopes, *Optics Communications*, Vol. 145, pp. 27-32, 1997.
11. L. Wald, Some Terms of Reference in Data Fusion, *IEEE Trans. on Geoscience and Remote Sensing*, Vol. 37, No. 3, pp. 1190-1193, 1999.
12. Z. Wang, A. C. Bovik, H. R. Sheikh and E. P. Simoncelli, Image Quality Assessment: from Error Visibility to Structural Similarity, *IEEE Trans. on Image Processing*, Vol. 13, No. 4, pp. 600-612, 2004.
13. C. Xydeas and V. Petrovic, Objective Image Fusion Performance Measure, *Electronic Letters*, Vol. 36, No. 4, pp.308-309, 2000.

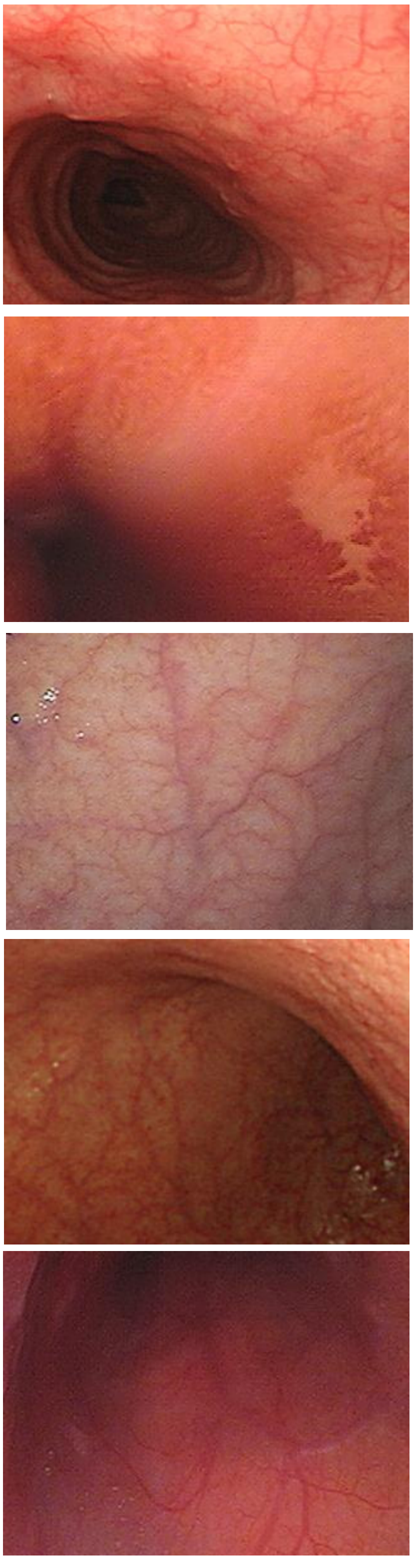

Figure 4. The original RGB color images (from top to bottom): L003, L051, L040, L049 and L032.

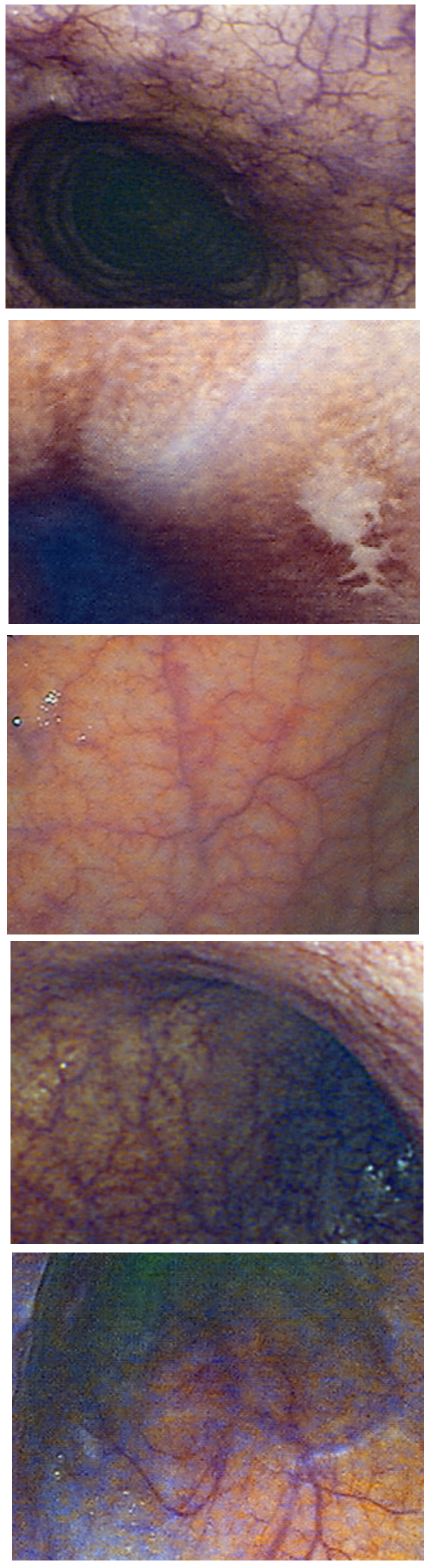

Figure 5. The fused RGB color images using the proposed method (from top to bottom): L003, L051, L040, L049 and L032.