Spectral Filtering for Color Discrimination Enhancement

Ken Nishino, Toyohashi University of Technology, Department of Information & Computer Sciences, 1-1 Hibarigaoka, Tempaku, Toyohashi, Aichi 441-8580, JAPAN
Arto Kaarna, Lappeenranta University of Technology, Department of Information Technology, P.O. Box 20, 53851 Lappeenranta, FINLAND
Kanae Miyazawa, Itoh Optical Industrial Co.,Ltd. 3-19 Miyanari-cho, Gamagori, Aichi 443-0041, JAPAN
Shigeki Nakauchi, Toyohashi University of Technology, Department of Information & Computer Sciences, 1-1 Hibarigaoka, Tempaku, Toyohashi, Aichi 441-8580, JAPAN

Abstract

A spectral filter is designed for enhancing the visual discrimination between two colors in a dataset. The filters are designed in spectral domain using spline interpolation through maximazing the color difference between the two selected colors. Two spectral datasets were applied in the design, the first dataset contained skin and vein colors from human arms. The second dataset consisted of facial colors with and without cosmetics. In the experiments the filters for both datasets were designed and the computational results showed clear enhancement in color differences for easier discrimination between the colors. The numerical results indicated that the proposed approach is reasonable for discrimination enhancement. The visual inspection of the RGB color images showed also enhancement even though the color differences in the test images were close to just-noticiable differences.

Introduction

The objective of this study is to define a spectral filter for spectral color datasets such that the difference between the two colors in a dataset can be visually enhanced. Then it would be easier and more reliable to discriminate the two colors from each other. The filter depends on the colors of the application, and thus, for each application, a new filter should be designed.

The purpose is to define the filters, one filter for each application, such that the visual perception of the color difference is larger than without the enhancement. A non-negative filter allows the manufacturing of a real filter or a mirror such that it performs the same enhancement in visualizing the difference. The manufacturing of a real filter is possible only with non-negative characteristics of the designed filter.

In a typical application the two colors look very similar, it might be difficult to distinguish them visually. This study shows, how to define a filter to make the color difference larger for more easy registration. Naturally this approach can be used also for the enhancement of originally larger color differences.

In principle, the similar approach has been used to simulate color vision deficiency [1]. The purpose was to filter the view such that the filtered perception was similar to human color deficient vision where the green and red colors are percepted similarly.

In [2], Karhunen-Loewe transform was applied to a spectral image to enhance the selected color. In the experiments, the proposed computational system gave clear visual enhancement.

Human skin color is one of the research fields attracting attention because it reflects rich information. In [3] some reflectance spectra at skin surfaces above a vein and on the surrounding tissue of human wrists were measured and evaluated in *xy*-chromaticity diagram. The reflectances above a vein were more bluish, but they, in comparison to the surrounding skin colors, expressed very small color differences.

In [4], the reflectance of human skin was measured. The skin color was considered to contribure to the chromophores in the skin, for example melanin, carotene and hemoglobin. Actually, the reflectance of human skin was obviously different from mannequin's skin.

The structure of this study is as follows. In the 2nd section we explain the problem setting. In the 3rd section, we give a general solution for the problem. The experimental data are described in the 4th section, the results from the experiments are in the 5th section, and the conclusions in the 6th section.

Problem Setting

The research problem in this study is to define a filter such that the filtering enhances the color difference between two spectral colors G_1 and G_2. In practise, G_1 and G_2 are spectral sets, i.e. each of them contains several similar spectra. Thus, the target is

$$max||C_1 - C_2|| \tag{1}$$

where C_1 contains the color information from the first spectral set G_1 and C_2 contains the color information from the second spectral set G_2. The difference function $||.||$ is ΔE_{00} using $L^*a^*b^*$ color space as defined by CIE [5]. The color sets C_1 and C_2 can be also considered as the human responses to the spectral reflectances of the samples. The design of the filters is performed in the spectral domain.

In the following we define a filter as a solution for Eq. 1. In the experiments, we will have two spectral color datasets. Each dataset has two spectral colors whose difference should be enhanced. Since the filter depends on the application, a filter for each color dataset is designed.

Spectral Design of the Filter

A spectral filter T can be used to modify the perception of colors. The filter is designed such that it enhances the visual color differences between two sets of colors, see Eq. 1. This is desirable in many practical applications, e.g. in facial makeup and in distinguishing blood vessels from skin. In the previous case a reflecting mirror would be desirable, and in the latter case a transparent filter would enhance human visual inspection. In general, the better discrimination of colors may result in higher quality, easier operation, and more reliable results depending on the application.

The purpose is to define filter T such that the color difference ΔE_{00} becomes larger between the two spectral sets G_1 and G_2.

The characteristics of a filter T are described as an interpolation polynomial. The optimization process has a set of the filter values as the independent variables and the full filter T is interpolated from these discrete values. Five different spectral discretation steps are used in the filter parameterization: 100nm, 60nm, 30nm, 20nm, 10nm, and 5nm. This means that the independent variables are discretized at these resolutions and interpolation is applied to resolve the characteristics between these wavelengths. At the high resolution of 5nm, interpolation is not applied, since that resolution is the maximum resolution for the filter characteristics. The purpose is also to find out which is the limit for high quality parameterization with low computational load in the filter design.

As soon as the filter T is defined, the spectral sets G_1 and G_2 are filtered with T to get the filtered spectra G_1^T and G_2^T. From these spectra the $L^*a^*b^*$ colors C_1 and C_2 are computed. Then the color differences ΔE_{00} between the two color sets C_1 and C_2 are calculated. Finally the average of all the color differences will be maximized. The computations in each iteration step of the optimization are

$$\begin{aligned}
&(G_1, G_2) \stackrel{T}{\rightarrow} \\
&(G_1^T, G_2^T) \stackrel{C}{\rightarrow} \\
&(L^*a^*b^*(G_1^T), L^*a^*b^*(G_2^T)) \stackrel{\Delta}{\rightarrow} \\
&\Delta E_{00}((L^*a^*b^*(G_1^T), L^*a^*b^*(G_2^T)) \qquad (2)
\end{aligned}$$

where $\stackrel{T}{\rightarrow}$ is the filtering operation, $\stackrel{C}{\rightarrow}$ is the color transformation, $C_1 = L^*a^*b^*(G_1^T)$, $C_2 = L^*a^*b^*(G_2^T)$, and $\stackrel{\Delta}{\rightarrow}$ produces information for the computation of color differences. The parameters of the filter T are updated such that the maximum for the average value of ΔE_{00} in Eq. 2 is found.

A filter is defined as a spline interpolation from the discrete values. Several interpolated filters with low resolution of 100nm and high resolution of 5nm are defined to secure two aspects in optimization. First, a low number of independent variables ensures the optimization process to converge faster. Secondly, a large number of independent varibles allows a more detailed description of the filter, and at the same time, better output from filtering. The implementation as an interpolated filter allows the consideration of these two contradictory requirements.

The discretation for the interpolation in the spectral domain is 100nm, 60nm, 30nm, 20nm, 10nm, and 5 nm within the visual range. The last discretation case reflects to a detailed filter while the first one allows a low number of independent variables in optimization.

In Fig. 1 the principle of the filter parameterization is displayed. In this example, the discretation is 100nm. Therefore there are four discrete points along the horizontal, the wavelength axis. These points are at wavelengths 400nm, 500nm, 600nm, and 700nm. The independent variables for the optimization are the filter values at those wavelenghts. Similarly the other discretizations are utilized in providing a larger number of independent variables, and thus, allowing more detailed filter design. In Fig. 1 the discrete points show the independent variables and the continuous line shows the interpolated filter values.

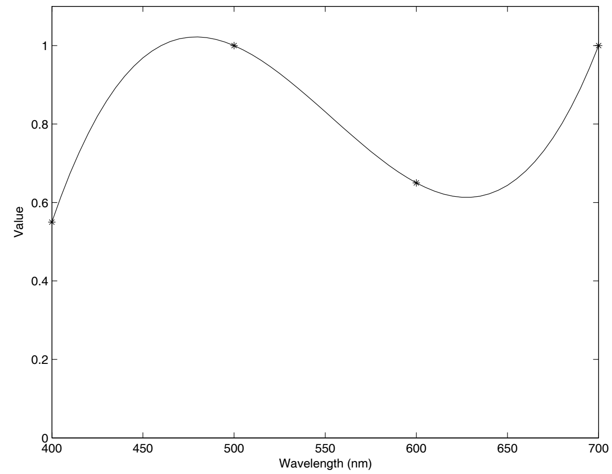


Figure 1. The principle of the filter discretation. '' refers to an independent variable in the optimization, continuous line refers to a spline interpolated filter.*

In the optimization the values of the independent variables are defined such that the maximun color error as defined in Eq. 2 is obtained. After interpolation the color values from the filtered spectra can be computed. Then these color values are used in the color difference computation.

Experimental data

The experimental data contains two datasets of spectral data. The datasets were measured in laboratory conditions using two spectral measuring systems.

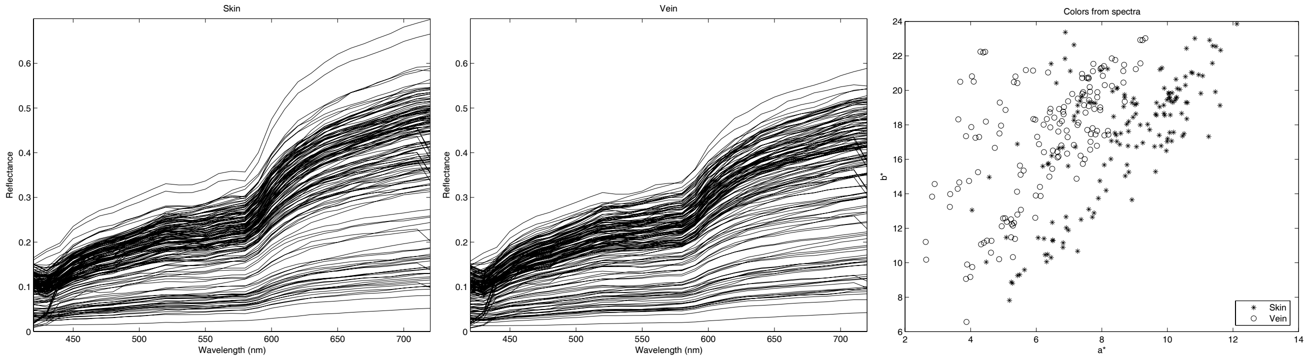
The measured spectra were divided into two sets: the training set and the test set. The training set consisted of selected spectra from every subject. The training set covers all variations of measuring conditions and subject color peculiarities. As a test set, the full spectral images were used. The test set has a large set of spectra that were not included in the training set. Thus, we had the training set and the test set which were mostly non-overlapping.

Skin and Vein

The first dataset consists of human arms showing both skin and veins. The images were measured using Nuance spectral camera, (Nuance^{TM} Multispectral Imaging System, CRI, VIS) [6]. The spectral range in the measurements was from 420nm to 720nm in 10 nm steps. After the measurements, the 5 nm resolution was obtained through interpolation. Totally 18 subjects were imaged.

One RGB-image of this set is shown in Fig. 2. The image shows an arm with skin and veins. The colors for these two sets are very similar and it is almost impossible to distinguish veins from the skin.

From the original spectral images a set of spectra were manually extracted such that the first set G_1 contained skin spectra and the second set G_2 contained vein spectra. The size of the training set was 304 spectra from 18 subjects, several spectra from each subject. The spectra from the training data is shown in Fig 3 a) and b). The a^*b^* chromaticities of these spectra are shown in Fig. 3 c). The light model used was D65. The chromaticities are very



a) b) c)

Figure 3. *Training spectral data of human skin and vein. a) skin. b) vein. c) Chromaticity coordinates a^*b^* from training spectra. '*' for skin, 'o' for vein.*

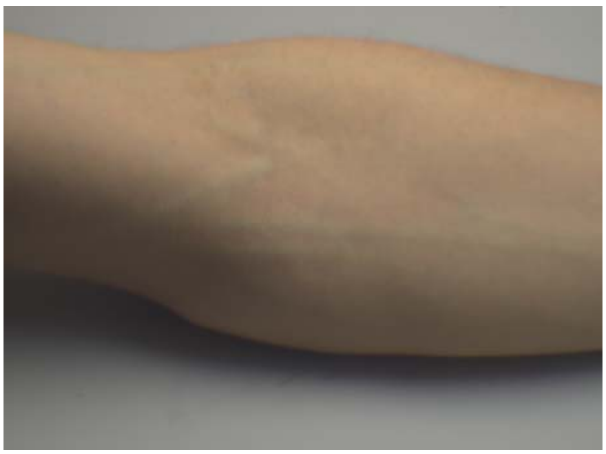


Figure 2. *RGB-image of the arm of one subject showing skin colors and veins.*

Figure 4. *RGB-image of the face of one subject. Some parts of the cheek without cosmetics.*

similar, thus showing similarity to Fig. 2.

Skin and Cosmetics

The measurements for this case were performed with a portable spectrophotometer, Color Spectrometer (CM-2002/Minolta) [7]. The cosmetics was of foundation type, Foundation (Maquillage Powdery UV/Shiseido, 10 colors).

Fig. 4 shows a typical application of the cosmetics applied to a face. The colors for facial skin and cosmetics in this case are very similar. The requirement for the filter is to better distinguish the areas with no makeup or poor makeup.

For this case the first set G_1 contained naked skin spectra and the second set G_2 contained spectra from skin where the foundation was applied to. The size of the sets were 364 spectra from 22 subjects, several spectra from each subject. The spectra sets are shown in Fig 5 a) and b). The a^*b^* chromaticities of these spectra are shown in Fig. 5 c). The light model applied was D65. The colors of the two sets are visually close to each other, see also Fig. 4.

Experimental Results

In the experiments we defined one filter for both test cases, one filter for skin and vein and one filter for skin and cosmetics. The filters were defined as described in the 3rd section using the experimental data described in the 4th section. The results are shown as color distributions and also as simulated images when the filtering has been applied to the original spectral images.

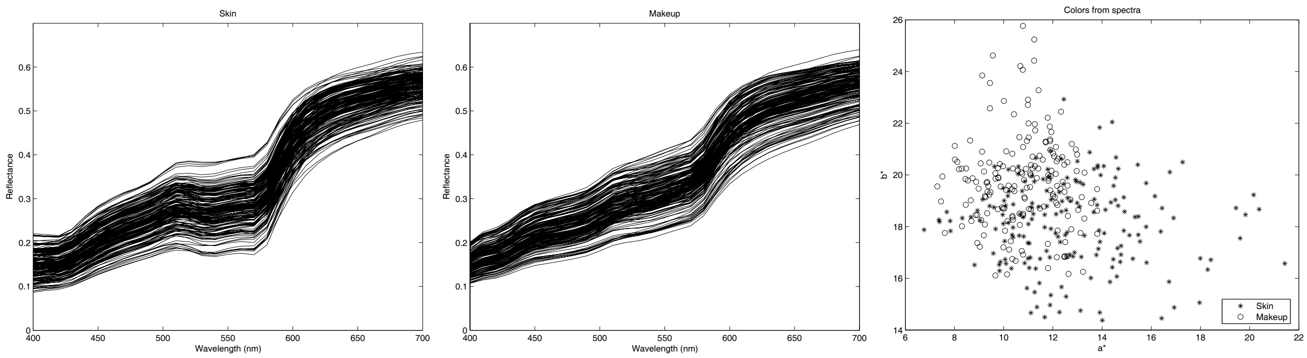
The color differences were computed between the skin samples and the vein samples of each subject separately. The samples were not mixed between the subjects. The skin colors and the vein colors for each subject varies and their cross-combination can not be justified. Also the changes in measuring conditions are minimized with this limitation.

The same approach was applied to the skin colors and the cosmetics colors. The color differences were computed within each subject only.

Skin and Vein

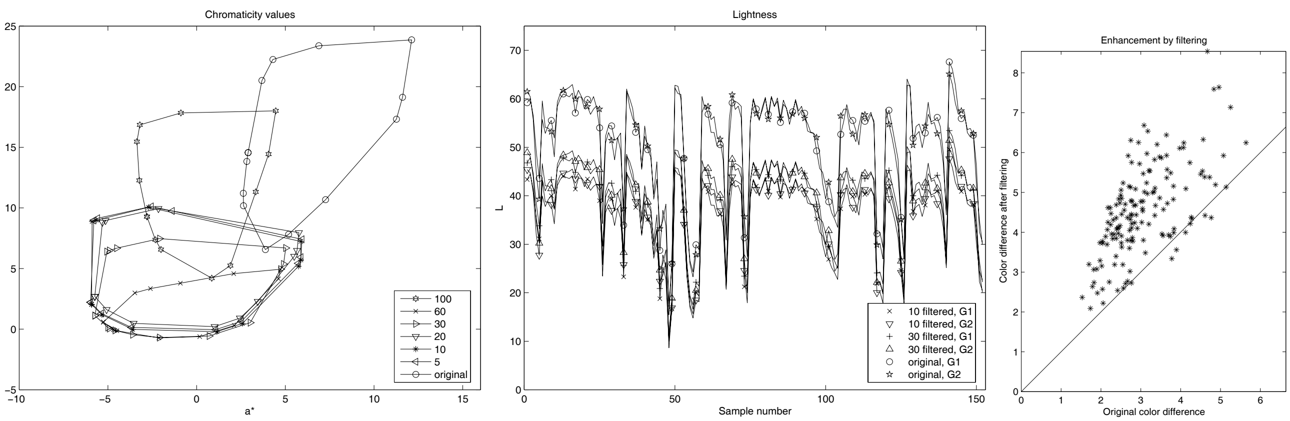
The optimization was performed as described in Eq. 2. The transmittances of all six filters designed with different resolutions from 100nm to 5nm are shown in Fig. 7. The continuous lines show the interpolated values for the filters. The values of the filters were limited to non-negative values only to allow physical implementation.

As soon as the filter T was defined it was possible to filter the spectral sets G_1 and G_2. Then the colors C_1 and C_2 of the filtered



a) b) c)

Figure 5. *Training spectral data of human skin and cosmetics. a) skin. b) cosmetics. c) Chromaticity coordinates* a^*b^* *from training spectra. '*' for skin, 'o' for cosmetics.*



a) b) c)

Figure 6. *Skin and vein. a) Convex hulls of chromaticities* a^*b^* *of the training spectra. Chromaticities both of the original spectra (center around* $a^* = 7$, $b^* = 17$*) and the filtered spectra (centers around* $a^* = 0$, $b^* = 5$*). One convex hull for each design resolution. b) Lightness values for training spectra, both original and filtered spectra. c) Color differences for training spectra. Horizontal axis: original differences, vertical axis: color differences after filtering. The color differences were calculated within each subject, not between the subjects.*

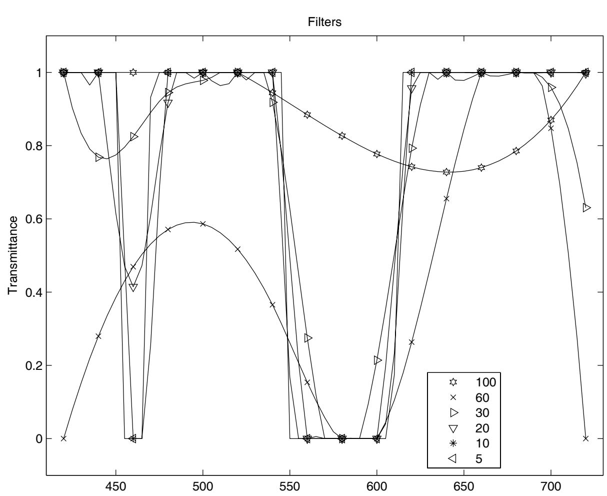


Figure 7. *Skin and vein. Interpolated filters. Design with resolutions 100nm, 60nm, 30nm, 20nm, 10nm, and 5nm.*

spectra were calculated. Fig. 6 a) shows the convex hulls of the colors C_1 and C_2 for the spectral sets in a^*b^*-chromaticity space. The original colors are within the convex hull marked with 'o', the center of this hull is close to $a^* = 7$, $b^* = 17$. Other convex hulls show the colors from the same sets filtered with various filters, see Fig. 7. The centers of these hulls are close to $a^* = 0$, $b^* = 5$.

In Fig. 6 b) the lightness L^* is shown for the original spectra sets and for the filtered sets. The filters were the ones designed with the spectral resolutions 30nm and 10nm.

Fig. 6 c) shows the color differences ΔE_{00} for the original spectra and for the filtered spectra. The filter applied was the one designed with 5nm resolution. The horizontal axis contains the original color differences and the vertical axis contains the color differences after filtering.

Finally in Fig. 8, the results with one test set are shown, the test set is a spectral image of one subject. Every spectrum from the image was filtered and then the RGB color values were calculated from the filtered spectra. The filter was the one designed with 5nm resolution. Light model D65 was applied.

Table 1 contains the average color differences in ΔE_{00} units. The third column contains the gains describing how large is the

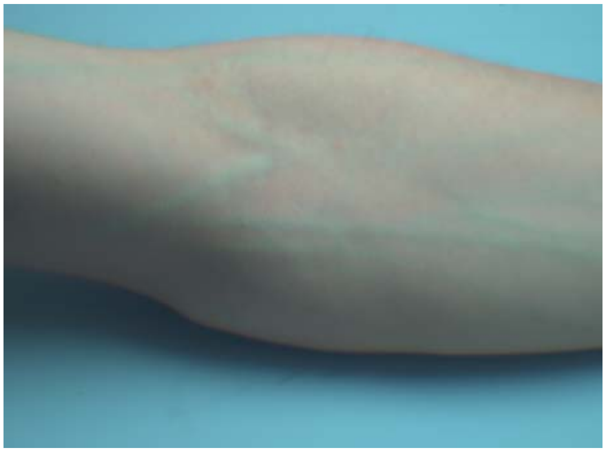


Figure 8. *Skin and vein. RGB-image of a filtered spectral image.*

change from the original color difference. The average color differences were computed for all designed filters. For this dataset the average of the original color differences in CIEDE2000 units was $\Delta E_{00} = 3.06$.

Table 1. Skin and vein. Average color differences ΔE_{00} and relative gains for the designed filters.

Discretation step	ΔE	Gain, %
100	3.413	11.5
60	3.620	18.3
30	4.346	42.0
20	4.475	46.2
10	4.506	47.2
5	4.539	48.3

Skin and Cosmetics

The same experiments were performed as with the previous dataset.

First, the filters based on various resolutions were defined for the dataset. The transmittances of all six filters designed are shown in Fig. 9.

Then, the color coordinates in $L^*a^*b^*$ color space were calculated for the filtered spectral sets G_1 and G_2. Fig. 10 a) shows the spectral sets in a^*b^*-chromaticity space. In Fig. 10 b) the lightness L^* is shown for the original spectra sets and for the filtered sets. The filters were the ones designed with the spectral resolutions 30nm and 10nm. Fig. 10 c) shows the color differences for the original spectra and for the filtered spectra.

Fig. 11 shows the results for one test set in this case. The whole spectral image was filtered and then the RGB color image was calculated. The filter used was the one designed with 5nm resolution and the light model was D65.

Table 2 shows the average color differences for all 6 filters designed. For this set the average of the original color differences in CIEDE2000 units was $\Delta E_{00} = 3.49$.

Conclusions

We have defined a procedure to enhance color differences for better perception. The procedure utilizes the spectral content of the images. The definition of the filters required spectral manipulation.

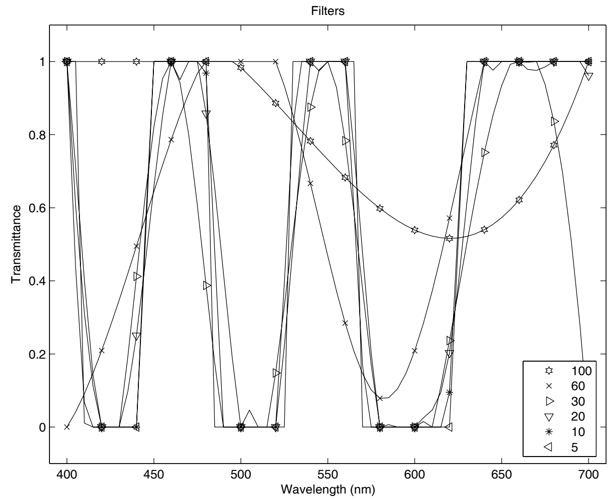


Figure 9. *Skin and cosmetics. Interpolated filters. Design with resolutions 100nm, 60nm, 30nm, 20nm, 10nm, and 5nm.*

Figure 11. *Skin and cosmetics. RGB-image of a filtered spectral image.*

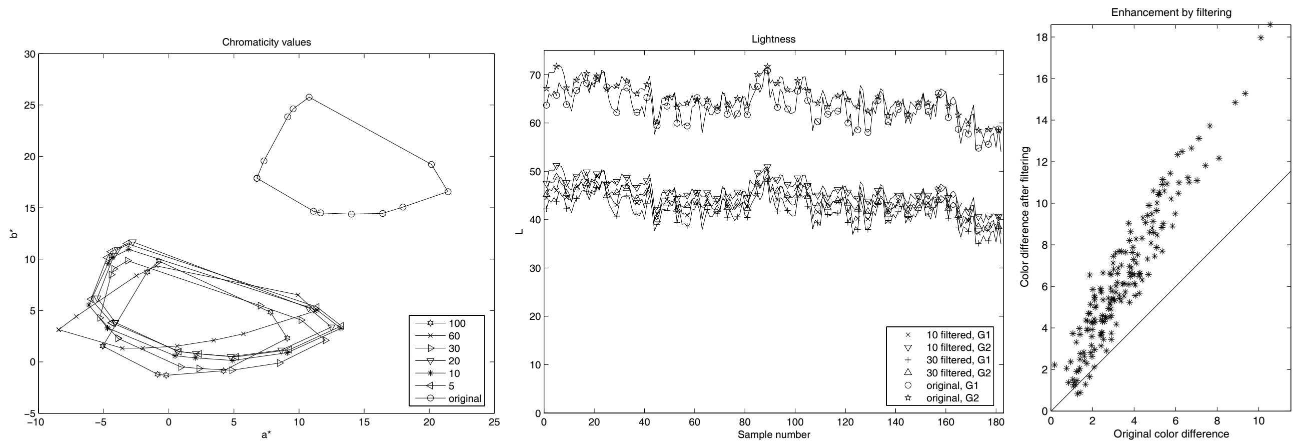
Table 2. Skin and cosmetics. Average color differences ΔE_{00} and relative gains for the designed filters.

Discretation step	ΔE	Gain, %
100	3.967	13.6
60	4.090	17.1
30	5.848	67.4
20	6.042	73.0
10	6.247	78.9
5	6.378	82.6

The following conclusions can be drawn.

The defined filters are like on-off filters with sharp edges, see Figs. 7, 9. A higher number of design variables in the filter definition allows more detailed filter design. Thus, the computational load is higher for the design of a high quality filter.

The colors from the filtered spectra are concentrated closer to origin in a^*b^* chromaticity space than the original colors, see



a) b) c)

Figure 10. *Skin and cosmetics. a) Convex hulls of chromaticities $a^* b^*$ of the training spectra. Chromaticities both of the original spectra (center around $a^* = 13$, $b^* = 20$) and the filtered spectra (centers around $a^* = 2$, $b^* = 5$). One convex hull for each design resolution. b) Lightness values for training spectra, both original and filtered spectra. c) Color differences for training spectra. Horizontal axis: original differences, vertical axis: color differences after filtering. The color differences were calculated within each subject, not between the subjects.*

Figs. 6 a), 10 a). The human color vision is more sensitive in this area than in the area of the chromaticities of the original spectra. Also the color distributions after filtering a larger than the original. At the same time the lightness values of the colors are lowered, see Figs. 6 b), 10 b).

Figs. 6 c), 10 c) shows the original color differences and the differences after filtering. Clearly, the filtering has enhanced the color differences between the two spectral sets. The numeric values in Tables 1, 2 also support this enhancement.

The filtered RGB images, see Figs. 8, 11, show that the discrimination between the skin and the veins, and between skin and makeup, respectively, has become easier. As such, the proposed approach is reasonable.

The filter design did not emphasize any special color difference ranges. In our future work, we will optimize filters for various difference ranges required in specific applications.

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Author Biography

Ken Nishino was born in 1984, and he received his Bachelor Degree at the Toyohashi University of Technology in Japan (2007). Currently he is a Master course student at Toyohashi University of Technology. His research interests include color and spectral imaging.

Arto Kaarna received his MSc degree (1980) in Mechanical Engineering, Licenciate of Technology degree (1990) and Doctor of Technology degree (2000) in computer science from Lappeenranta University of Technology (LUT), Finland. Currently he is working as an acting professor in media in networks with LUT. His main research interests are in color and spectral image processing and in imaging information in networks.

Kanae Miyazawa received her BSc in physics from Japan Women's University (1995) and her PhD in engineering from Saitama University (2001). She was a postdoctoral researcher at the University of Joensuu, Finland (2001-2003). Since 2003 she has worked at Toyohashi University of Technology, Japan and since 2006 she has also worked at Itoh Optical Industrial Co., Ltd. Her research interests include functional spectral filter. She is a member of the Japan Society of Applied Physics.

Shigeki Nakauchi received his B.E. and M.E. degrees in information and computer sciences from Toyohashi University of Technology, Toyohashi Japan, in 1988 and 1990, respectively, and his Ph.D degree in systems and information systems from Toyohashi University of Technology, Toyohashi Japan in 1993. He is currently Professor in the Department of Information & Computer Sciences, Toyohashi University of Technology, Toyohashi Japan. His research interests include color perception and color imaging technology. He is a member of Optical Society of America (OSA), Institute of Electronics, Information and Communication Engineering (IEICE), Japan Neural Network Society (JNNS), The Society for Imaging Science and Technology (IS&T), Japan Neuroscience Society and Vision Society of Japan.