Optimal Design of Camera Spectral Sensitivity Functions Based on Practical Filter Components

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Abstract

A new approach to obtain the optimal set of spectral sensitivity functions from among the complete combinations of the given practical filter components is presented. The criteria to select the optimal set are Vora and Trussell's μ-factor and the proposed UMG colorimetric quality factor. Comparative computation results show that μ-factor is not an appropriate metric for the optimal design of camera spectral sensitivity functions while UMG is able to pick out the optimal design successfully. Furthermore, the ultimate optimal set has been found by selecting the most optimal set in terms of μ-factor from the sub-optimal collection obtained with UMG. This hierarchical approach considers comprehensively the advantages of both quality factors. The candidates of the optimal set based on the given filter components are presented in the end of the paper.

Introduction

The human visual color perception can be described by a tristimulus theory that involves the linear combination of three different photoreceptor types with known spectral sensitivities in visible range. The CIE has characterized the standard human visual color perception with color-matching functions for a standard observer and defined standard color spaces, including nonuniform CIE XYZ and uniform CIE L*a*b* spaces. These standards are fundamental for colorimetry and for the transformation and sharing of color information. Color input devices such as cameras and scanners that seek for colorimetric color reproduction (including color appearance match) of object colors must take into account the characteristics of the human visual system in their design and in the understanding of the output data from the physical sensors. Although these input devices have reached reasonable performance today, their color reproduction is still perceptibly different from the original scene. Major reasons for this are the difficulties of selection and fabrication of transmittance filter sets that are suitable for color imaging devices. Basically two primary factors - the non-Luther condition due to the practical limitations in manufacturing these curves and the intrinsic imaging noise in the use, limit their color accuracy. The optimal design of the spectral sensitivity functions should account for both factors. A criterion for evaluating and optimally designing the spectral sensitivities are therefore desirable.

The concept of the so-called "quality factor" was first introduced by Neugebauer.[3] About ten quality metrics have been proposed up to now. If we categorize all the metrics for evaluating and designing spectral sensitivities striving for colorimetric reproduction, we could have two primary types. The first type describes the geometrical difference between the subspaces of color matching functions and spectral sensitivity functions. These quality factors are often sample-independent and do not consider the imaging noise, and only considers the difference through linear transformation. Typical metrics are Neugebauer's q-factor,[3] for the evaluation of single imaging channel, Vora-Trussell's extension, μ-factor,[4] for the colorimetric evaluation of multispectral system with an arbitrary number of channels, and the CQF ("Color Quality Factor"),[6] already used in the industry, also for the colorimetric evaluation of whole imaging channels. The second type describes the minimal color error for a set of user-defined samples of reflectance spectra in CIE color spaces. The linear transformation from RGB signal to XYZ values is determined by minimizing the color error and a data-dependent metric can be defined upon this procedure. Imaging noise may or may not be considered during the minimization. In this category, there are Shimano's Q_{st} and Q_{sf} metrics,[20, 21] minimizing the average color error in CIE XYZ space without noise consideration, Tajima's indices,[5] taking account of object color spectral characteristics of principle components, Hung's CRI (Color Rendering Index),[15] and Sharma-Trussell's Figure of Merit (FOM),[6] probably the most extensive and complicated quality factor, minimizing the color error in a perceptually uniform color space while taking account of the white noise in the recording process. Quite a few simpler quality factors can be attributed to the special forms of FOM.[6] We have extended the FOM as "UMG" (Unified Measure of Goodness) so that it includes both the signal-independent and signal-dependent imaging noise (dark noise and shot noise), as well as multi-illuminant color correction, as described in the following section. Notice that the data-dependent metrics may perform well for specific data sets and may not perform well for some other data sets. Selection of standard set in the computation should be cautious and consistent. The 24 Macbeth ColorChecker patches are used as standard samples in our computation because of our analysis as well as the widespread use of this target in similar researches.

A lot of effort has been put on the filter design. Ohta started the evaluation and optimization of sensitivities in subtractive imaging systems.[1,2] Wolski, et al reviewed the major work done before them,[7] including Davies and Wyszecki,[17] Engelhardt and Seitz,[18] Vrhel and Trussell,[10] Vora and Trussell.[4,11] Tsumura, et al optimized three channel Gaussian-shaped filters with noise presence by simulated annealing to minimizing CIE color difference.[19] Wolski et al also optimized the sensor response functions for colorimetry of reflectance and emissive objects under multiple illuminants,[7] and the optimization is carried out in CIE Lab color space with smoothness constraint. Sharma and Trussell also did optimal searching of transmittance filters,[22] but not with their proposed FOM, they were looking for the nonnegative filters with the presence of white noise in the similar way as Vrhel and Trussell.[10] Notice that all of those efforts were successful in some aspects, but also have some individual disadvantage. A satisfactory solution should take account of both data-independent and data-dependent performance, as well as signal-independent and signal-dependent noise, and the objective function of optimization should be implemented within a perceptually uniform color space or color appearance space. Furthermore, most of these studies give virtual optimal curves, which need be approximated with manufacturer's filter component set during fabrication process. This approximation will induce error so that the fabricated curves are deviated from the ideally optimal ones, which may make the theoretically optimal set practically not optimal at all. The optimal design approach would optimize the imaging channels directly as a parameterized model of the filter manufacturing process, e.g. the selection of the filter components with its thickness used in each channel. We will follow this strategy to optimize filters for a high-end digital camera. In this case, it is unnecessary to assume the spectral sensitivities be smooth, since in practice most are not strictly smooth, and the designed spectral sensitivities are guaranteed to be non-negative, because the filter components used are always non-negative.

In this paper, one data-independent metric, μ-factor, and one data-dependent metric, FOM or UMG are chosen as criteria to optimal design of spectral sensitivities for colorimetric reproduction. Both metrics will be discussed briefly, followed by the description of the application with our analysis. Results from both metrics are reported and compared.

The Colorimetric Quality Factors

Vora and Trussell's μ-Factor

The Luther condition requires that the spectral sensitivities be the linear combinations of the color matching functions.[13] This strict relationship may not easily follow in the real world, but the closer the approximation is, the better performance in the colorimetric reproduction is expected. μ-Factor introduced by Vora and Trussell characterizes this geometrical difference, and is widely discussed. Basically it describes the spatial difference between the fundamental subspaces of the color matching functions and camera spectral sensitivities:

$$\mu_A(S) = \frac{\mathrm{Trace}\left\{O^T U U^T O\right\}}{\mathrm{Trace}\{U U^T\}} \qquad (1)$$

where A and S are the matrices of the color matching functions and camera spectral sensitivity functions, O and U are the corresponding fundamental subspaces. Similar equation without using the orthonormal space concept can also be used to characterize this difference.[12] This is an elegant relationship, but it's incomplete to deal with practical problems, i.e., the noise issue. It is easily to fabricate highly colorimetric sensitivity set but with poor practical colorimetric reproduction, because the sensitivities amplify noise too much in the signal processing chain. Noise is intrinsic in the imaging process, and they can be found commonly existing in the following forms: photon noise, dark current noise, fixed pattern noise, photo response non-uniformity noise, reset noise, $1/f$ noise and quantization noise.[23,16] In our application, the following noise model was used:

$$E(noise:\eta) = 0 \qquad (2)$$

$$\mathrm{var}(noise:\eta) = \sigma_d^2 + \rho^2 \mu_i = \sigma_d^2 + \rho^2 \sigma_i^2 \qquad (3)$$

where σ_d^2 is the dark noise variance, σ_i^2 is the shot noise variance, and ρ is the total quantum efficiency coefficient. The noise will be propagated and amplified by serial linear and nonlinear transformations in the following signal processing chain (Figure 1).

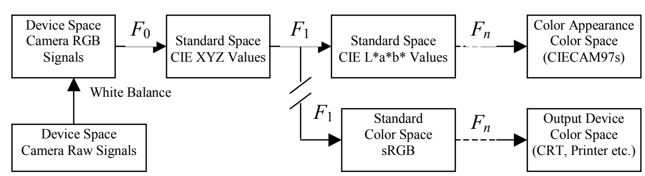


Figure 1. Processing pipeline of digital camera signal, where F_s are transformations

UMG ("Unified Measure of Goodness")

We have designed a new metric by taking account of the following properties: Mean color difference for an ensemble of standard reflectance samples in uniform color space is minimized; The input signal together with noise, which includes shot noise and floor noise, is propagated into the target color space, and a linear matrix is obtained through optimization based on the noise propagation property. Furthermore, a strategy relevant to multi-illuminant color correction is proposed.

Assuming the average color difference as Euclidean distance in target color space is minimized using the following cost function:

$$\varepsilon = E\left\{\left\| F(t) - F(F_0 t_c)\right\|^2\right\} \tag{4}$$

where F_0 linearly transforms camera output signals into CIE XYZ values, t is the measured CIE XYZ values, t_c is the camera output signal with noise in Eqs. (2-3), and

$$F(\bullet) = F_n(\cdots F_2(F_1(\bullet))) \tag{5}$$

sequentially transform tristimulus values into the interested target color space, i.e. CIE Lab, or CIECAM97s via linear or nonlinear transformations $F_{0, \ldots} F_n$. For deriving our metric, F_0 is assumed to be a linear matrix in deriving our metric, however in reality, a lot of techniques can be implemented to do this transformation, including polynomial transformation, look-up table etc. If $F_1 \ldots F_n$ are approximately differentiable with continuous first partial derivatives, a first-order Taylor series provides a fairly accurate locally linear approximation for each of them:

$$F_i(x + \Delta x) - F_i(x) = J_{F_i}(x)\Delta x \tag{6}$$

With the law of chains for first derivatives,

$$F(x + \Delta x) - F(x) = \prod_{i=1}^{n} J_{F_i}(F_{i-1}(\cdots F_1(x)))\Delta x = J_F(x)\Delta x \tag{7}$$

Therefore,

$$\varepsilon = E\{\left\| J_F(t)(t - F_0 t_c)\right\|^2\} \tag{8}$$

By minimizing this color error, the optimal linear matrix F_0 can be determined, and a new measure for single viewing-taking illuminant pair can be defined as Eqs. (9-11):

$$\varepsilon_{\min} = \alpha(A_L) - \tau(A_L, G) \tag{9}$$

and

$$q(A_L, G, F) = \frac{\tau(A_L, G)}{\alpha(A_L)} \tag{10}$$

$$\theta = 1 - \sqrt{1 - q(A_L, G, F)} \tag{11}$$

Since the taking (recording) and viewing illuminant may be different, we may define a quality factor for any taking and viewing illuminant pair. For particular application, if we have a set of illuminants $\{L_{v_1}, L_{v_1}, \cdots, L_{v_n}\}$ to be chosen as the viewing illuminant, and another set of illuminants $\{L_{t_1}, L_{t_1}, \cdots, L_{t_m}\}$ to be chosen as the taking illuminant, we can define a quality factor matrix M as follows:

$$M = \begin{bmatrix} \theta_{11} & \theta_{12} & \theta_{13} & \cdots & \theta_{1m} \\ \theta_{21} & \theta_{22} & \theta_{23} & \cdots & \vdots \\ \theta_{11} & \theta_{11} & \theta_{11} & \cdots & \vdots \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ \theta_{n1} & \theta_{n2} & \theta_{n3} & \cdots & \theta_{nm} \end{bmatrix} \tag{12}$$

The comprehensive quality factor *UMG* for the taking-viewing-illuminant pair may be defined as the weighted average of elements of the above matrix:

$$\Theta = \frac{1}{nm}\sum_{i=1}^{n}\sum_{j=1}^{m} w_{ij}\theta_{ij} \quad \text{while} \quad \sum_{i=1}^{n}\sum_{j=1}^{m} w_{ij} = 1 \tag{13}$$

where w_{ij} is the weight determined by camera manufacturers, quantifying the importance of the corresponding quality factor θ_{ij} for viewing-taking-illuminant pair (L_{v_i}, L_{t_j}).

Notice that UMG requires much more computation amount than μ-factor (about 10 times), since UMG needs to calculate the multiple statistical quantities for all object samples in the training set. It is recommended to avoid large-scale UMG computation.

The Application

A high-end B/W digital camera system, Roper Scientific Photometric Quantix, was purchased recently at the Munsell Color Science Laboratory. The color filters were not yet designed for the camera. In this practical application, multiple channel spectral sensitivity functions will be determined from a set of available bandpass filters, infrared filters and longpass glass filters. Known data are the total quantum efficiency of the electronic sensor, and the transmittance spectra of these filter components. Optimal three to five spectral sensitivity functions for colorimetric reproduction are expected.

The normalized total B/W detector quantum efficiency (or the spectral sensitivity function) is measured on the spot, which includes the spectral sensitivity of CCD sensor, the transmittance of the optical lenses and IR cut-off filter, as shown in Figure 2(a). This B/W sensitivity is measured according to certain setup of the camera. And the sensor sensitivity is constant once the configuration is kept fixed.

There are 14 band-pass glass filters (VG-type and BG-type Scott). In general the thickness is 3mm, and the transmittance is shown in Figure 2(b). These filters are important to shape the green and blue channels for digital cameras when they are combined with long-pass filters. It is possible to yield red channel as well if combined with infrared filters.

There are 7 infrared cut-off glass filters (2 BG-type, 5 KG-type Scott), whose transmittance is shown in Figure 2(c) when the thickness is 3mm. The two BG-type filters have rich variation from 400nm to 650nm, while the five KG-type filters varies from 600nm to 700nm, but changes slowly between 400nm and 600nm, which is a crucial wavelength interval for color image capturing.

The transmittance of the 19 long-pass cut-off glass filters (GG-type, OG-type and RG-type Scott) is shown in Figure 2(d), where the thickness is still 3*mm*. Their transmittance spectra typically have sharp edges and do not vary too much if the filter thickness changes (1 - 3*mm*).

The transmittance of all these filters is based on a thickness of 3*mm*, which can be easily varied to 2*mm* and 1*mm* according to the manufacturer, and according to

Bouger's Law, the corresponding transmittance can be represented as, for 2*mm* and 1*mm* thickness:

$$T_{2mm} = T_{3mm}^{2/3},\ T_{1mm} = T_{3mm}^{1/3} \qquad (14)$$

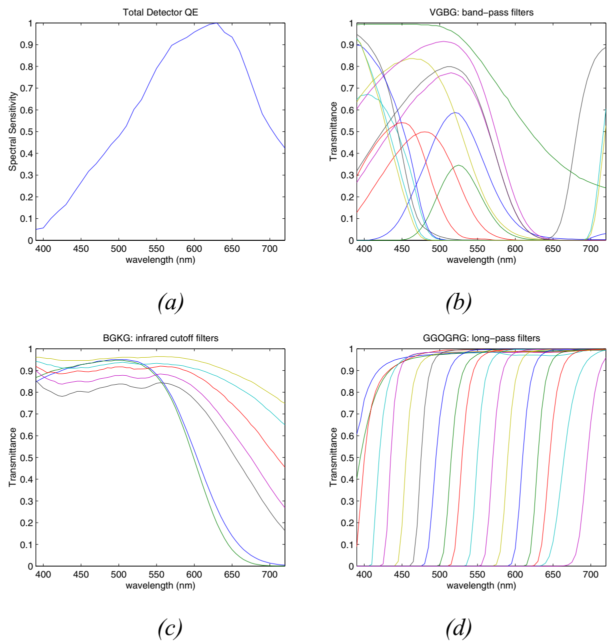


Figure 2. (a) CCD QE curve; (b) Transmittance spectra of bandpass filter elements; (c) Transmittance of infrared filter elements (d) Transmittance of longpass cutoff filter elements

If a composed filter of certain channel is obtained by superimposing several filter elements with different thickness, its total transmittance can be written as:

$$T_{Total} = \prod_{i=1}^{k} T_i^{x_i/3} \qquad (15)$$

where x_i is the thickness of the corresponding filter element. So the total channel spectral sensitivity function including CCD quantum efficiency curve is

$$SS = QE_{CCD} \cdot T_{total} \qquad (16)$$

To achieve the transmittance of blue and green channel sensitivities, let the band-pass filters have thickness choices of 3*mm*, 2*mm* and 1*mm*, optionally combined with long-pass filters. The BG-type of IR filters are more useful than the KG filters, and the thickness of each basic IR can choose from 3*mm*, 2*mm* and 1*mm*, totally 21 IR filters. Thickness variation of long-pass filters does not change their transmittance shape very much, so only thickness of 3*mm* (or 2*mm* / 1*mm*) may be selected to reduce computation amount, but totally we have 57 longpass filters if we change the thickness. To obtain the transmittance of red spectral sensitivity function, use the combination of long-pass filters and IR filters, or the combination of band-pass filters and IR filters. All possible filter combinations can be formed as following:

Band-pass: 14×3=42 (may be independently used)
IR: 7×3=21 (not used independently)
Long-pass: 19×3=57 (may be independently used)
Band-pass × IR: 42×21=882
Band-pass × Long-pass: 42×57=2934
Long-pass × IR: 57×21=1197

The total number of all filters is 4572.

To find the optimal *K* filters from among these filters, the total combination is 4572^K, for example, the computation iterations would be 9.56×10^{10} for *K*=3.

It can be seen that even for searching three optimal filters from the set, the computation will take too much time. Some pre-analysis on the filter information has to be carried out in order to finish the search in reasonable time.

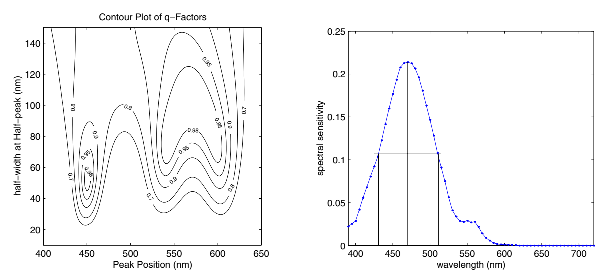
Pre-selection of Spectral Sensitivity Functions

It's a huge computation load to obtain an optimal set with a brute force search. We need to pre-select filters in the first step to reduce computation. Our early research[24] on general optimization of hypothetical spectral sensitivity functions shows that, filters with single primary peak are preferred, and the possible peak position of blue channel is located between 400nm and 500nm (strictly 420 – 470nm), that of green channel between 500nm and 600nm (strictly 520 – 560nm), that of red channel between 550nm and 650nm (strictly 570 – 620nm), as shown in Figure 3(a). The choices of blue channel become 517, and for green channel, 1869, for red channel, 1368 if the extended peak position ranges are applied. This will lead to the reduction of the amount of computation to 517 × 1869 × 1368 = 1.3219×10^9, much less than the raw brute force search. If the strict peak position ranges of the three channels are used, the three numbers are further reduced to 391, 1075 and 1049. The corresponding computation load (4.409×10^8) is even less because the search range is even smaller. However, some good combinations may be discarded.

For better performance under noisy environment, the widths of sensitivity functions cannot be too wide, or too narrow. From our previous experience, optimal sensitivity functions should limit their half-peak width to less than 120nm. By assuming the area of the enclosed rectangle be half of the area under the single-peaked sensitivity curve, the full-width at peak-peak can be easily estimated (Figure 3(b)), the possible filters with width of less than 120nm and strict peak position ranges are then obtained. The possible choices for blue, green and red channels are now reduced to 384, 601 and 402. They contribute total enumeration to 9.2 $\times 10^7$, which is a reasonable computation amount able to be finished within days for current desktop personal computers.

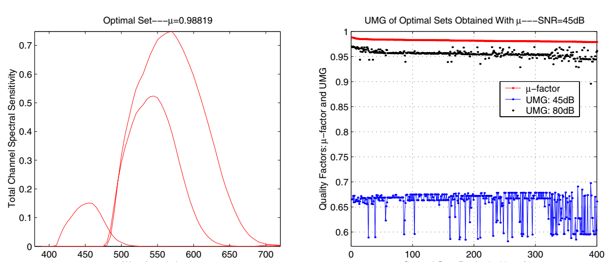
Optimization with μ-factor

In our initial trials, 400 optimal combinations will be obtained with μ-factor since the evaluation of μ-factor is much faster. The corresponding UMG values are calculated for the 400 sets by assuming SNR be 45dB or 80dB (noise≅0), which is more or less a reasonable performance for most color imaging devices. The most favorable set of three filters in terms of μ-factor is shown in Figure 4(a), but these kind of weird shapes are not preferred from our intuition, since the transmittance of green channel is totally enveloped under red channel. Examining all 400 sets, most of them have such kind of unfavorable shapes. They have high μ-factor (>0.98), but the UMG values when SNR = 45dB is not good (<0.70). When the noise is free from the system (SNR=80dB), it's no surprise that the set of sensitivity functions with high μ-factor corresponds to high UMG values, although their shapes are not ideal like the "optimal" set given here. It seems the true optimal and desired filter sets with smaller μ-factor values are buried among those "pseudo" optimal sets. In order to dig out the optimal set, we reduce the searching range by using only one width for the longpass filters, i.e. 2*mm*, because width does not affect their cutoff properties very much. The choices for red, green and blues channels are now 114, 206 and 150. Still we find the first 400 optimal sets in terms of μ-factor in the first step, and then calculate the corresponding UMG when SNR is set at 45dB for the 400 sets.



(a) *(b)*

Figure 3. (a) Preferred peak Positions and half-width; (b) Estimating the half-maximum width for any spectral sensitivity functions with single primary peak

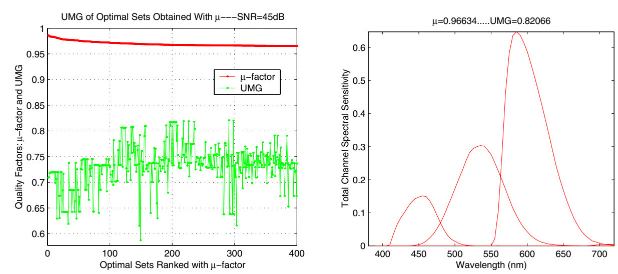


(a) *(b)*

Figure 4. (a) The "optimal" sensitivity function set obtained with μ-factor, shape is not optimal; (b) the UMG and μ-factor values of the 400 "optimal" sets

Figure 5(a) demonstrates the different trends of μ-factor and UMG values. The μ-factor values are very close for all of these sets (>0.965), but obviously, some sets have much higher UMG values than the others. The set of filters with highest UMG value among the 400 sets are shown in Figure 5(b). Its UMG is 0.82 (45dB) and μ-factor is 0.966. Quite a few similar sets have close UMG and μ-factor values. Their shapes are very similar to this optimal one and can be treated as alternative optimums. Most of the other sets with high μ-factor values but low UMG values do not have such kind of reasonable shape, but their shapes are like Figure 4(a), which are not preferred, but sensitivity sets such as Fig. 5(b) are better results than that from our first trial.

From the process we can see that when the noise is superimposed onto signal like in real world (the signal-to-noise ratio is about 30-50dB), these optimal sets can perform better than the other sets. Furthermore, when the noise becomes too much (the signal-to-noise ratio reduces to about 15dB, i.e. in dark), they do not show overwhelming noise proofing any more, since the noise has overshadowed the input signal. If the SNR goes too high (>70dB), the noise can be omitted, filter sets with high μ-factor values tend to perform well in terms of color difference.



(a) *(b)*

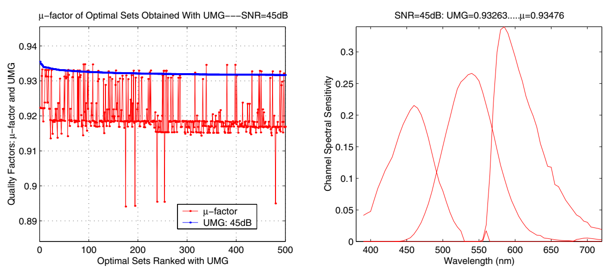
Figure 5. (a) UMG of the 400 sets obtained with μ-factor, only 2mm thickness is used for longpass filters; (b) The optimal set

Optimization with UMG

Our third trial is to optimize the spectral sensitivities functions by directly evaluating UMG for the 92 million combinations. Since UMG dependents on data set, illuminants, and noise level, these parameters are kept the same as the previous experiments. As expected, it takes very long to go through all combinations, a Pentium III 550MHz computer required about twenty days, comparatively, it only required about one day to finish the evaluation with μ-factor. Figure 6 shows the optimal set obtained from this approach, which is selected with μ-factor from among the 500 sets obtained with UMG. This optimal set has a μ-factor value of 0.935, smaller than the optimal set shown in Figure 5, but its UMG performance is much better, 0.933. The difference between the two sets is that, the sensitivities in Figure 6 have closer peak sensitivities than that in Figure 5. It would be interesting to know, which would perform better in practice. This has to be further determined with additional properties, or chosen by professional manufacturers.

Discussion

The fine-tuning of optimal spectral sensitivities may include some extra properties. Different weights may be assigned to different metrics. In addition, the optimization of four or five spectral sensitivities can be carried out based on the optimization results of three channels. This paper has shown that the optimal three channels can have good colorimetric performance, adding one or two channels can obtain more information on object colors, and thus have a larger quality factor value. The peak positions of the additional spectral sensitivity functions should locate differently from the peak positions of the available ones in order to reduce noise amplification and maximize acquisition information for multi-spectral imaging of object reflectance. Further results will be demonstrated in the future.



(a) *(b)*

Figure 6. (a) μ-Factor of 500 optimal filter sets obtained with UMG; (b) The optimal set with maximal UMG value

Conclusions

An optimal set of filters should satisfy both conditions: first, the subspace of the camera spectral sensitivity functions should approximate that of color matching functions with maximal possibility; and second, the estimation of object colors from noise-mixed channel signals should be close to the measurement of these object colors in uniform color space. Basically, μ-factor indicates whether a sensitivity set is colorimetric or not in noiseless world. But in real world, noise may discard some pseudo colorimetric sets. By taking account of more practical factors, UMG is able to pick out genuine colorimetric sensitivity functions. It can be shown that a set of sensitivity functions with poor μ-factor can have reasonably good UMG and can reproduce object colors quite well; and a set of sensitivity functions with highest μ-factor may correspond to low UMG value, which means it may not be a good choice to be implemented in practice.

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