Filter Selection for Multispectral Color Image Acquisition

Jon Y. Hardeberg▲
Gjøvik University College, Gjøvik, Norway

The quality of a multispectral color image acquisition system depends on many factors, the spectral sensitivity of the different channels being one of them. In a relatively common setup, a multispectral camera is being implemented by coupling a monochrome digital camera with a set of optical filters, typically mounted on a filter wheel. The properties of these filters is an important component of the system design. Different methods have been proposed for the design or selection of appropriate filters. In this article we review several methods used for selection of an optimal subset of filters from a set of available filters. The different filter selection methods are subjected to a comprehensive evaluation procedure, in which their quality is evaluated mainly in terms of the ability of the resulting system to reconstruct scene spectral reflectances.

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Introduction

A relatively common approach to acquiring multispectral color images is to use a monochrome digital camera coupled with a set of color filters, as shown in Fig. 1. Given the spectral radiance of the light source and the spectral sensitivity of the camera including the optics, then the spectral sensitivity of the different channels of the acquisition system is determined by the spectral transmittances of the filters. The quality of a multispectral color image acquisition system depends on many factors, the spectral sensitivity of the different channels, and thus the choice of filters, being one of them.

The design of optimal filters given an optimization criterion has been proposed by several authors.[1–8] A drawback with such methods is the cost and difficulty involved in the practical production of the optimized filters.

Another approach encountered in many existing multispectral scanner systems is to use a set of heuristically chosen color filters, which are typically equispaced over the visible spectrum.[9–14] Although promising results are reported using such systems, there is reason to believe that the choice of filters remains suboptimal for a given task.

An intermediate solution can be used where the camera filters are selected from a set of available filters.[1,2,15–17] This choice can be optimized, for example by taking into account the statistical spectral properties of the objects that are to be imaged, as well as the spectral transmittances of the filters, the spectral characteristics of the camera, and the spectral radiance of the illuminant. The main idea is to choose the filters so that, when multiplied with the illuminant and camera characteristics, they span the same vector space as the reflectances that are to be acquired in a particular application, as suggested earlier, e.g., by Chang et al.,[18] Schmitt et al.,[19] Vora and Trussell,[20] and Mahy et al.[21]

In the following sections we present different methods for selecting filters. The different selection methods are then subjected to a comprehensive evaluation procedure, in which their quality is evaluated mainly in terms of the ability of the resulting system to reconstruct scene spectral reflectances.

Filter Selection Methods

In this section we present different methods for selecting a subset of $\tilde{K}$ filters out of a set of K available filters. We suppose the spectral transmittances $\phi_k(\lambda)$, $k = 1...K$, of the filters, as well as the spectral sensitivity $\omega(\lambda)$ of the camera to be known. After combining these functions, we represent the filters (or more precisely the associated camera channel sensitivities) by the vectors $\mathbf{y}_k$,

$$\mathbf{y}_k = \alpha_k[\phi_k(\lambda_1)\omega(\lambda_1)...\phi_k(\lambda_N)\omega(\lambda_N)]^t, \qquad (1)$$

for $k = 1...K$. The normalization factors α_k are typically[16] chosen such that $\|\mathbf{y}_k\| = 1$.

The goal is then to select, among a set of K available color filters, a subset of $\tilde{K}$ filters being well suited for our application.

Equispacing of Filter Central Wavelengths

A simple, heuristic, strategy is to choose a set of filters where the dominant wavelengths are relatively equally spaced throughout the visible spectrum. This approach is being used in many current multispectral color imaging systems,[9–14] for instance the VASARI scanner implemented at the National Gallery in London used seven broad-band,

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▲ IS&T Member

jon.hardeberg@hig.no

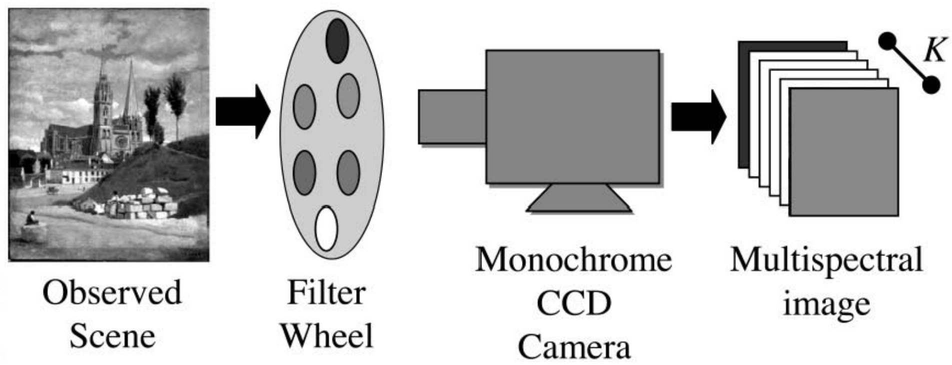

Figure 1. A common setup of a multispectral color image acquisition system using a filter wheel.

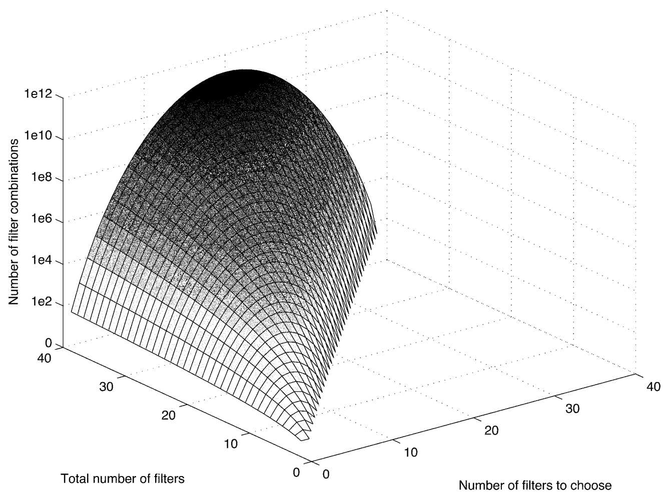

Figure 2. Illustration of the computational complexity involved when comparing all possible filter combinations from a set of real filters. Note the logarithmic ordinate axis.

nearly Gaussian filters covering the visible spectrum in its original configuration.[12,14]

Exhaustive Search

In this selection method all possible filter combinations are evaluated. Given any optimization criterion, this approach can give the optimal set of filters. However, the complexity of such an approach could be prohibitive, since it requires the evaluation of

$$n_c = \binom{K}{\tilde{K}} = \frac{K!}{\tilde{K}!\left(K-\tilde{K}\right)!} \tag{2}$$

filter combinations. For a small number of filters, this method may be applicable, see, e.g., Yokoyama et al.[22] who evaluates the $n_c = 80730$ combinations needed for a selection of $\tilde{K} = 5$ filters from a set of $K = 27$, or Vora et al.[1,2] who selects $\tilde{K} = 3$ filters from a set of $K = 100$ Wratten filters, requiring $n_c = 1.6 \times 10^5$ filter combinations. However, when the number of available filters, as well as the number of filters to be chosen increase, the complexity grows considerably, as shown in Fig. 2. For the example presented by Maître et al.,[15] where $K = 37$ and $\tilde{K} = 12$, the number of filter combinations to be evaluated would attain $n_c = 1.8 \times 10^9$, while a selection of 12 filters out of 100 would require 10^{15} combinations.

Maximizing Orthogonality in Characteristic Reflectance Vector Space

This method, first proposed by Maître et al.,[15] and later modified by Hardeberg[16] is more physically related to the problem which we have to solve, since it takes into account the spectral properties of the available filters, the acquisition system, as well as the statistical spectral properties of the surfaces that are to be imaged.

The central idea of the method is to select filters that have a high degree of orthogonality after projection into the vector space $R(\mathbf{U}^{(r)})$ spanned by the r most significant characteristic reflectances $\mathbf{u}_i$, $i = 1 \ldots r$, calculated by Principal Component Analysis (PCA) of a set $\mathbf{R}$ of sample reflectances. The matrix

$$\mathbf{U}^{(r)} = [\mathbf{u}_1 \mathbf{u}_2 \ldots \mathbf{u}_r],\ r \leq \mathrm{rank}(\mathbf{R}) \tag{3}$$

thus represents the orthonormal basis of the vector space $R(\mathbf{U}^{(r)})$.

The projection of the kth filter on the jth characteristic reflectance vector is $\mathbf{u}_j^t \mathbf{y}_k$ and its projection in $R(\mathbf{U}^{(r)})$ is denoted as the $r \times 1$ coordinate vector $\mathbf{g}_k = \mathbf{U}^{(r)t}\mathbf{y}_k$. Note that $\mathbf{g}_k$ corresponds to the camera responses through the kth filter to a set of characteristic reflectances $\mathbf{U}^{(r)}$.

By this algorithm, given the choice of the number of characteristic vectors r that are taken into account, we can choose a set of $\tilde{K}$ filters, having spectral transmittances of $\phi_k(\lambda)$, $k = k_1, \ldots, k_{\tilde{K}}$ as follows:

STEP 1: Considering the set of projections $\mathbf{g}_k$, $k = 1 \ldots K$, we choose as the first basis vector $\mathbf{y}_{k_1}$ the one which transfers most energy from the r most significant characteristic reflectances:

$$k_1 = \arg_k \max_{1<k<K} \left\| \mathbf{g}_k \right\| \tag{4}$$

That is, the filter that transfers most energy from the characteristic reflectances is chosen.

STEP 2: The second filter $\mathbf{y}_{k_2}$ is then the filter whose projection onto $R(\mathbf{U}^{(r)})$ has a maximal component orthogonal to $\mathbf{g}_{k_1}$:

$$k_2 = \arg_k \max_{\substack{1\leq k\leq K \\ k\neq k_1}} \left\| \mathbf{g}_k - \mathbf{g}_{k1n}\left(\mathbf{g}_{k1n}^t \mathbf{g}_k\right) \right\| \tag{5}$$

where $\mathbf{g}_{k_1 n} = \mathbf{g}_{k_1} / \left\| \mathbf{g}_{k_1} \right\|$.

STEP i: Let $\mathbf{G}^{(i)} = [\mathbf{g}_{k_1}, \mathbf{g}_{k_2},...,\mathbf{g}_{k_{i+1}}]$ denote the projections of the i first selected filters in $R(\mathbf{U}^{(r)})$. The filter $\mathbf{y}_{k_{i+1}}$ is then chosen such that its projection $\mathbf{g}_{k_{i+1}} = \mathbf{U}^{(r)t}\mathbf{y}_{k_{i+1}}$ has the largest component orthogonal to the space $R(\mathbf{G}^{(i)})$.

The orthonormal basis of $R(\mathbf{G}^{(i)})$ spanned by the selected filters projected onto the characteristic reflectance space is denoted $\mathbf{G}_n^{(i)}$. It could be determined easily by a Singular Value Decomposition (SVD) applied to $\mathbf{G}^{(i)}$. However, this would imply a complete recalculation of the basis for each iteration. We propose to determine it in an iterative manner as follows. The first component is determined simply in step 1 by $\mathbf{G}_n^{(i)} = \mathbf{g}_{k_1 n}$. For the ith iteration step, $\mathbf{G}_n^{(i)}=[\mathbf{G}_n^{(i-1)}\mathbf{g}_{in}]$, where

$$\mathbf{g}_{in} = \frac{\mathbf{g}_i - \mathbf{G}_n^{(i-1)}\left(\mathbf{G}_n^{(i-1)t}\mathbf{g}_i\right)}{\left\|\mathbf{g}_i - \mathbf{G}_n^{(i-1)}\left(\mathbf{G}_n^{(i-1)t}\mathbf{g}_i\right)\right\|} \tag{6}$$

We then choose the $(i + 1)$th basis vector $\mathbf{y}_{k_{i+1}}$ for the $\boldsymbol{k} = \boldsymbol{k}_{i+1}$ that maximizes the following expression:

$$k_{i+1} = \arg_k \max_{\substack{1\le k\le K \\ k\notin\{k_1,k_2,\ldots,k_i\}}} \left\|\mathbf{g}_k - \mathbf{G}_n^{(i)}\left(\mathbf{G}_n^{(i)t}\mathbf{g}_k\right)\right\| \tag{7}$$

We note that this selection method has one free parameter, r, the number of characteristic reflectances that are used to define the vector space $R(\mathbf{U}^{(r)})$ onto with the projections are done.

Evaluation Procedure

In order to evaluate the quality of the proposed filter selection algorithms, it is necessary to consider the quality of the resulting multispectral color image acquisition system in its entirety. This system quality depends on many factors, and is closely related to the task the system is supposed to solve. For example, designing an imaging system for discriminating objects based on spectral reflectance[21] requires different sensitivities than a system in which the goal is to achieve a highest possible colorimetric accuracy.

To evaluate the resulting systems, we report and compare the average RMS spectral estimation error $d = \|\mathbf{r} - \tilde{\mathbf{r}}\|$ over the colors of a test target, as well as the maximal RMS spectral estimation error. These metrics present the advantage of being simple and general. To complement, we also report the average and maximal ΔE^*_{ab} using the D65 illuminant for the colorimetric calculations. This metric obviously has the advantage of being closely related to human color perception, but on the other hand it has several serious limitations, illustrated for example by the fact that it does not pick up any difference between metameric spectra. Other quality measures could also have been used.[20,23–27] Depending on the intent, these may be based on colorimetric or spectral properties, on mean or maximal errors in a data set, or alternatively on critical samples for which the reconstruction quality is particularly important for a specific application. Imai et al.[27] argue wisely that a combination of quality measures should be used.

In our model, the reflectance spectrum is estimated from the camera responses by a linear model[16] in order to minimize the expected RMS spectral estimation error on a set of representative reflectances. If the $\tilde{K}$ -channel camera response to a spectral reflectance $\mathbf{r}$ is modelled by $\mathbf{c}_{\tilde{K}} = \mathbf{Y}^t\mathbf{r}$, and the spectral estimation task as $\tilde{\mathbf{r}} = \mathbf{Q}\mathbf{c}_{\tilde{K}}$, then this estimation operator is given by

$$\mathbf{Q} = \mathbf{R}\mathbf{R}^t\mathbf{Y}(\mathbf{Y}^t\mathbf{R}\mathbf{R}^t\mathbf{Y})^{-1} \tag{8}$$

We could also have used other methods for estimating the spectral reflectance from the camera response values, such as the one proposed recently by Ribés et al.[28,29]

Results and Discussion

For our simulations we have defined a camera system in which the spectral sensitivity corresponds to what we would typically achieve with a CCD camera under tungsten light, see the dotted lines in Fig. 3. For the filter selection method which takes into account *a priori* information about the type of reflectances that are going to be imaged (see above), we used a target of 64 oil paints prepared by the National Gallery.[16] For additional evaluation purposes, we also used a database of spectral reflectances of 218 colored samples collected from nature.[30,31]

In a first experiment we selected five filters from a set of 20 Hoffman filters, using four different selection methods. The first method employed a heuristic approach (see above), in which the filters were chosen manually, in order that the resulting peak sensitivities were approximately evenly distributed over the visible spectrum. In the second method, we maximized the orthogonality, using the parameter $r = 5$. The final two methods employed an exhaustive evaluation of all possible filter combinations in order to minimize the mean RMS and the maximal ΔE^*_{ab} respectively. The resulting spectral sensitivities of the camera channels are shown in Fig. 3, while the spectral and colorimetric estimation errors are reported in Table I. As an illustration, we show in Fig. 4 four examples of spectral reflectances from the database, along with the spectral estimations using the four different filter sets.

We observe that the difference in mean RMS spectral estimation error is not particularly large between the selection methods. The maximal ΔE^*_{ab}, however, varies significantly. The overall best result when considering all four quality metrics seem to be achieved with the combinatorial method minimizing $\Delta E_{\max}$. Examining the channel sensitivities of Fig. 3 we note that, as expected, the maximum orthogonality methods yields peak sensitivities that are distributed over the entire wavelength interval; however, they are not equally spaced. We also note that the sensitivities do not fall off to zero at the extremes of the wavelength interval we are using in our models. In a practical system this should obviously be avoided, typically by extending the wavelength interval and introducing an IR cutoff filter.[16]

In order to evaluate the quality of the filter sets when used for a different task than what they were optimized for, we simulate an alternative system in which the same camera is used to acquire images of natural objects under D65 daylight. The same four filter sets selected before are used, but the reconstruction operator is established with the new sensitivities and reflectance database according to Eq. (8). From the results reported in Table II, we see that all the filter sets yield poorer performance compared to when used with the original database and illumination. The most serious degradation is found with the filter set selected by the combinatorial method minimizing the mean RMS error. This is not unexpected, given the overlapping sensitivities as shown in Fig. 3. The filter set obtained with the combinatorial method minimizing $\Delta E_{\max}$ yields the overall best performance.

In a second experiment we started with a set of 20 Hoffman filters and 15 Kodak Wratten filters. By allowing each final channel filter to be a combination of two filters, this gave us a total 630 filter transmittances to choose from. However, many filter combinations are not feasible since the resulting transmittance factor is too low. We therefore

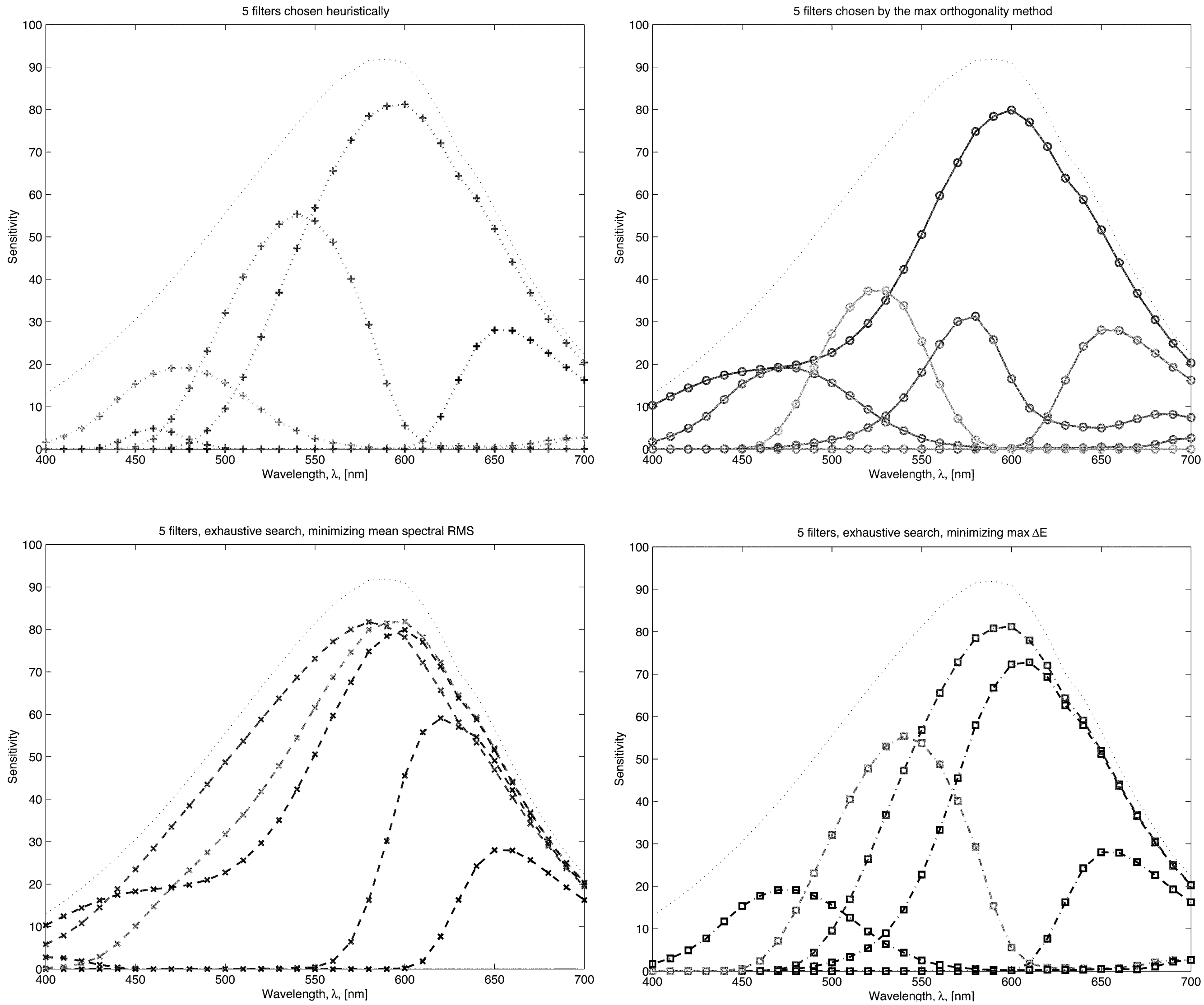

Figure 3. Spectral sensitivities of the resulting camera channels obtained by selecting 5 Hoffman filters with 4 different selection methods. The stapled line represents the joint spectral sensitivity of the camera and the illuminant.

TABLE I. Quality metrics for the different selection methods, applied to the selection of 5 out of 20 Hoffman filters. The method which maximizes the orthogonality performs better than the heuristic approach when considering the spectral estimation error, while the combinatorial method always gives optimal results with regards to its optimization criterion.

Selection meth.	RMS	RMS_{max}	ΔE	ΔE_{max}
Equispacing	0.0121	0.0472	1.14	5.09
Max orthog.	0.0114	0.0483	1.51	9.72
Comb. RM S	0.0101	0.0447	2.55	13.37
Comb. ΔE_{max}	0.0106	0.0466	0.45	2.39

TABLE II. Quality metrics for the different selection methods, when the filters sets are evaluated for a different acquisition task than the one they were optimized for. The filter set obtained with the combinatorial method minimizing ΔE_{max} seems to be the most robust.

Selection meth.	RMS	RMS_{max}	ΔE	ΔE_{max}
Equispacing	0.0197	0.0785	1.61	10.55
Max orthog.	0.0212	0.0893	3.23	19.02
Comb. RM S	0.0177	0.0682	4.93	96.14
Comb. ΔE_{max}	0.0170	0.0610	1.24	6.53

proceeded to a preselection of filters by eliminating the filter combinations which yielded a transmittance factor of less than one percent. This left us with 181 filters to choose from. In Tables III and IV we report the resulting estimation errors when selecting from 3 to 12 filters with the algorithm presented above. In Table III we set the parameter $r = \tilde{K}$ for each selection, while in Table IV we chose the value for r which minimized the resulting average RMS error.

Several observations can be made from these results. First, if we consider the results for five filters, the average RMS error is indeed reduced, compared to when only single filters were used (Table I), although the other measures are actually increased. Secondly, we note from comparing Tables III and IV that setting the parameter $d = \tilde{K}$ is not far from optimal.

Furthermore, we see as expected that the estimation errors decrease rapidly with increasing number of filters. With 9

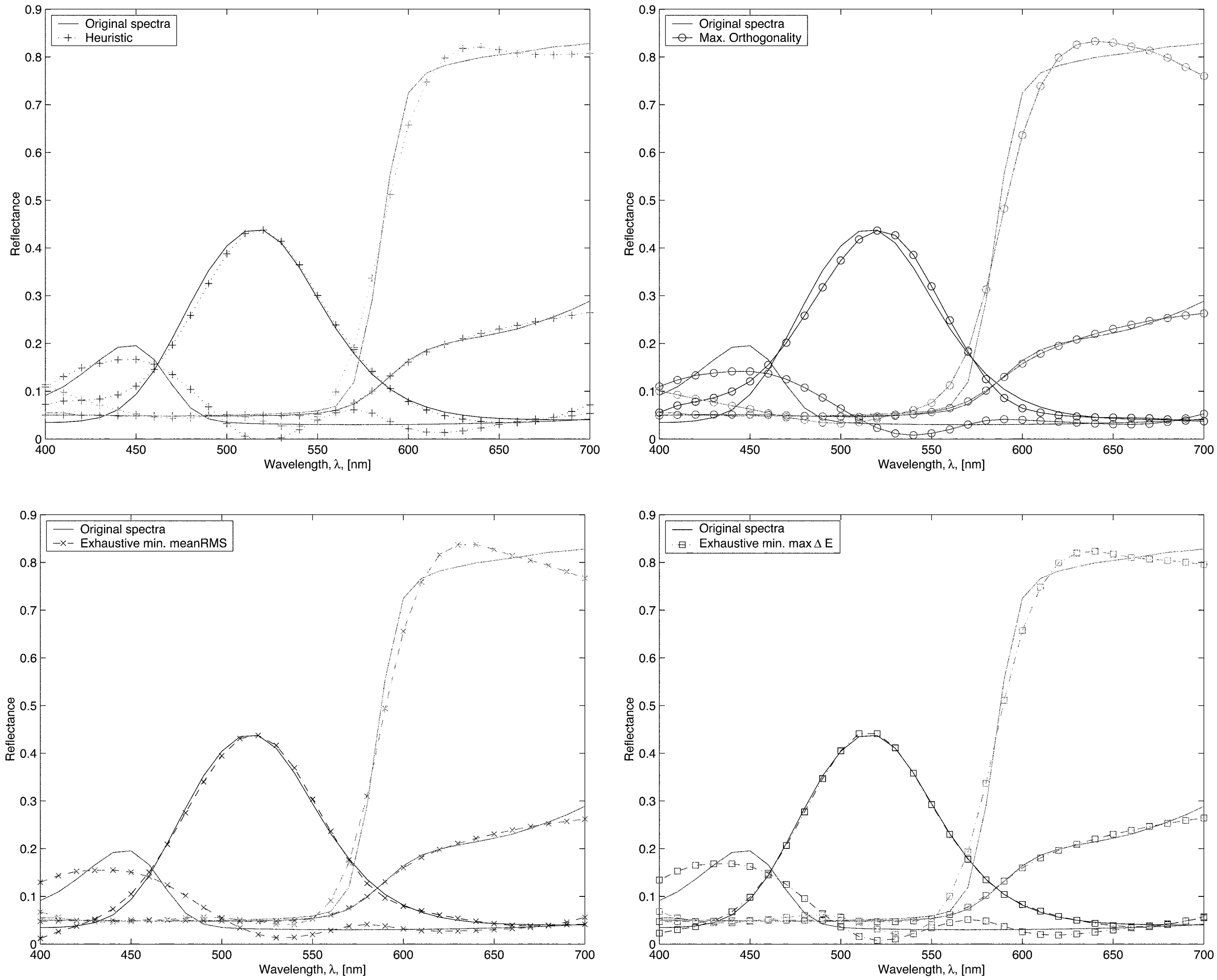

Figure 4. Spectral reflectance estimation of four example reflectances from the database (Emerald green, Ultramarine, Red ochre, Mercuric Iodide) using different filter sets with five filters.

TABLE III. Results for the selection method which maximizes the orthogonality in characteristic reflectance space, applied to the selection out of a basis of 181 filters created by combinations of two Wratten and Hoffman filters.

$\tilde{K}$	r	RMS	RMS_{max}	ΔE	$ΔE_{max}$
3	3	0.0265	0.0768	12.70	75.89
4	4	0.0165	0.0506	2.34	14.68
5	5	0.0104	0.0485	1.64	14.31
6	6	0.0080	0.0261	0.99	3.96
7	7	0.0057	0.0192	0.47	2.29
8	8	0.0040	0.0166	0.15	0.74
9	9	0.0032	0.0166	0.16	1.12
10	10	0.0023	0.0080	0.06	0.60
11	11	0.0016	0.0049	0.04	0.24
12	12	0.0013	0.0050	0.03	0.15

TABLE IV. Results for the selection method which maximizes the orthogonality in characteristic reflectance space. The parameter *r* is chosen between 3 and 15 as the one which minimizes RMS.

$\tilde{K}$	r	RMS	RMS_{max}	ΔE	$ΔE_{max}$
3	13	0.0253	0.0771	7.05	27.43
4	12	0.0160	0.0498	2.43	11.92
5	5	0.0104	0.0485	1.64	14.31
6	5	0.0077	0.0336	0.98	8.80
7	15	0.0055	0.0166	0.49	2.43
8	8	0.0040	0.0166	0.15	0.74
9	5	0.0031	0.0130	0.15	1.01
10	10	0.0023	0.0080	0.06	0.60
11	11	0.0016	0.0049	0.04	0.24
12	11	0.0012	0.0040	0.02	0.09

filters the maximum ΔE^*_{ab} estimation error reaches 1. It is important to keep in mind, however, that these results are obtained with a simulated camera discarding noise. In a real system, when noise is present, it is not necessarily beneficial to increase the number of filters too much.[16,32]

Conclusion

One of the factors that determine the quality of a multispectral color image acquisition system is its spectral sensitivity. In a relatively common setup a multispectral color image acquisition system is implemented by coupling

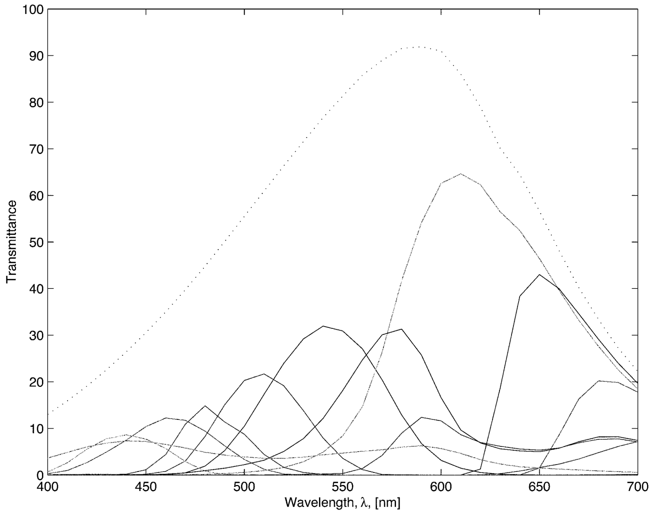

Figure 5. Spectral sensitivities of the resulting camera channels obtained by selecting 12 filters out of a set of 180 combined Hoffman and Wratten filters.

a monochrome digital camera with a set of optical filters, typically mounted on a filter wheel. Together with the spectral sensitivity of the sensor and the spectral radiance of the illumination, spectral transmittances of the filters determine the system spectral sensitivity.

We have reviewed and compared several methods for the selection of an optimized subset of filters from a set of available filters. The presented methods present several advantages and disadvantages. An optimal solution given any optimization criterion can in theory be achieved with an exhaustive search approach, in which all possible filter combinations are evaluated, but this method tend to be prohibitive in terms of computational complexity when the number of filters is large.

A faster method is proposed, in which the filters are chosen sequentially in order to maximize their orthogonality in a characteristic reflectance space representative of the application area for the system. This method is found to yield good results, although suboptimal. In practice, an adequate solution might be to first use this method to select a set of more filters than needed, and then apply the exhaustive search method to reduce the set to the desired number of filters.

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