Spectral Imaging Model by XYZ+K Four-Band Filter

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Abstract

*Spectral imaging has advanced to reproduce the real colors under different illuminants. Since the high-precision spectral camera is expensive, multi-band cameras with 6~16 channels have been widely used. On the other hand, human vision is basically tri-chromatic and perceives a color based on metamerism. According to matrix-**R** theory, any spectral input **C** is decomposed into fundamental **C*** and metameric black **B**. Human vision perceives the fundamental **C*** as visible component but bypasses the metameric black **B** as invisible component. On the conditional color matching under a fixed illuminant, we need only the fundamental. However both of fundamental and metameric black are necessary under the different illuminants, because the objective spectrum **C**=**C***+**B** changes with the illuminant. This paper proposes a new spectral sensing model with XYZ+**K** four-band filters. The additional filter **K** is designed to rescue the "metameric black" and restores the spectral reflectance in combination with "fundamental" captured by XYZ colorimetric tri-color filters. The paper clarifies the mathematical design concept for the spectral sensitivity curve of filter **K** based on matrix-**R** theory and shows how the proposed XYZ+**K** sensing model works well when applied to the parametric or non-parametric spectral estimators keeping with the colorimetric color reproduction. The paper also introduces a simulation on spectral image restoration under the different illuminants.*

Introduction

Since high-precision spectral camera is expensive, the multi-band system[1-3] supported with spectral estimation algorithms[4-7] from low-dimensions have been developed actively. Singular Value Decomposition (SVD), Principal Component Analysis (PCA) or Wiener estimation methods provided a mathematical solution to this direction. However, the most of multi-band cameras have the following questions in the spectral design of multi-band filters.

[1] The spectral sensitivity design rule is unclear and choice of filter set is often empirical.

[2] The multi-band signals are not compatible with *XYZ* colorimetric reproduction.

LabPQR is a spectral CMS model for answering these questions. Lab plus PQR reflects the colorimetric plus metameric black components. However, it needs multi-band camera for encoding the spectral input to LabPQR[8]. Once encoded to LabPQR, it works excellent in the colorimetric to spectral inverse estimation with trained color chips.

The proposed model introduces a minimum set of *XYZ*+***K*** four-band filters, where an additional filter ***K*** is designed to save the "*metameric black*" and restores the spectral reflectance in combination with "*fundamental*" captured by *XYZ* colorimetric tri-color filters. Different from LabPQR, the model needs neither spectral input camera nor encoding process but directly recovers the spectral input from the *XYZ*+***K*** four-band signals.

The projection from spectral to tri-color space is many-to-one and non-invertible. Cohen[9] derived the *matrix* ***R*** to project *n*-dimensional spectrum onto *3*-dimensional *HVSS* and clarified how it extracts the "*fundamental*" and ignors the "*metameric black*". But both are necessary for the spectral imaging under the different illuminants.

In the previous paper[10, 11], the author proposed a simple method for the spectral estimation from *XYZ* using a strong correlation with the *metameric black*. It was useful for the specified color media such as photography or inkjet prints with the trained parameters but was substantially impossible to discriminate the metamers, because the *XYZ* system is blind to the *metameric blacks*. Since the "*fundamental*" is carried by *XYZ* value, first of all, the new model captures it by *XYZ* filters and next tries to rescue the lost "*metameric black*" by the additional filter "***K***"[12].

The paper clarifies a spectral design of filter "***K***" based on *matrix* ***R*** theory and shows how it's useful for spectral recovery in compatible with colorimetric reproduction.

Fig.1 illustrates the basic concept of proposed *XYZ* plus ***K*** filter system for spectral imaging.

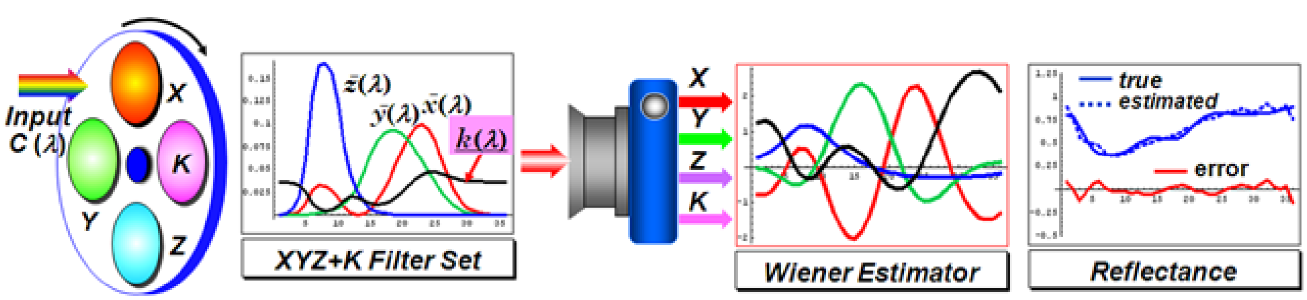

***Figure 1** Conceptual Model of Spectral Recovery from XYZ plus **K** Filter system*

Four-Band Model: Why *XYZ* +"*K*"?

According to the *matrix-R* theory, a *n*-dimensional color spectrum ***C*** is decomposed into the *fundamental* ***C**** (visible) and the *metameric black* ***B*** (invisible) as

$$\begin{aligned} &\boldsymbol{C}=\boldsymbol{C}^{*}+\boldsymbol{B},\ \boldsymbol{C}^{*}=\boldsymbol{R}\boldsymbol{C},\ \boldsymbol{R}=\boldsymbol{A}(\boldsymbol{A}^{t}\boldsymbol{A})^{-1}\boldsymbol{A}^{t} \\ &\boldsymbol{B}=\boldsymbol{R_K}\boldsymbol{C},\ \boldsymbol{R_K}=\boldsymbol{I}-\boldsymbol{R};\ \boldsymbol{I}=identity matrix \end{aligned} \quad (1)$$

Where, ***R*** denotes $n \times n$ projector onto HVSS derived from CIE color matching matrix ***A***.

The tri-stimulus value ***T*** =*XYZ* carries the *fundamental* ***C**** that is the essential spectrum to human vision, while the *metameric black* ***B*** is neglected as invisible with zero-stimulus.

Letting a *XYZ* input be $\boldsymbol{T_{65}}$ taken by *sRGB* camera for an input spectrum $\boldsymbol{C_{65}}$ under the illuminant $\boldsymbol{D}_{65}$, the *fundamental* $\boldsymbol{C_{65}}^*$ is invertible from $\boldsymbol{T_{65}}$ by pseudo-inverse projection as

$$\begin{aligned} &\boldsymbol{C}_{65}=\boldsymbol{C}_{65}^{*}+\boldsymbol{B}_{65},\ \boldsymbol{T}_{65}=\boldsymbol{A}^{t}\boldsymbol{C}_{65}=\boldsymbol{A}^{t}\boldsymbol{C}_{65}^{*} \\ &\boldsymbol{C}_{65}^{*}=\boldsymbol{P_{inv}}\boldsymbol{T}_{65},\ \boldsymbol{P_{inv}}=\boldsymbol{A}(\boldsymbol{A}^{t}\boldsymbol{A})^{-1} \end{aligned} \quad (2)$$

Eq. (2) means the *XYZ* tri-color filter tacitly captures the *fundamental* spectrum $\boldsymbol{C_{65}}^*$.
While, the *metameric black* $\boldsymbol{B_{65}}$ is obtained by applying the projector $\boldsymbol{R_K}=\boldsymbol{I}-\boldsymbol{R}$ to input $\boldsymbol{C_{65}}$ as

$$\boldsymbol{B}_{65}=\boldsymbol{R_K}\boldsymbol{C}_{65},\ \ \boldsymbol{R_K}=\boldsymbol{I}-\boldsymbol{R} \quad (3)$$

The proposed model is equipped with a popular *XYZ* and the additional forth filter ***K*** to capture the *metameric black*. The filter ***K*** should have the spectral transmittance just same as projector $\boldsymbol{R_K}$. However it's unrealistic to imitate $\boldsymbol{R_K}$ exactly, because $\boldsymbol{R_K}$ is a 2-D matrix with *n*-3 freedom of dimension (n=36, $\Delta\lambda$=10 nm: λ=380~730nm).
Hence, the proposed model drastically reduces the dimension of $\boldsymbol{R_K}$ to minimum 1-band filter ***K***. Since the *fundamental* is exactly restored from *XYZ* filter designed to satisfy *Luther condition*, the final spectral error mainly depends on the estimation accuracy of the *metameric black*. Fig.2 illustrates why the forth filter should be "***K***" if compatible with colorimetric reproduction and if allowed to add one more filter at least, and shows how to estimate the spectral input from *XYZ*+***K*** filter set.

Design of Forth Filter "*K*" based on Matrix R

Although it's hard to save the exact the *metameric black* $\boldsymbol{B_{65}}$ only by the 1-D filter ***K***, the model approximates the projector $\boldsymbol{R_K}$ by paying attention to the following structural features.

(a) The *j*-th row vector $\boldsymbol{B}_j$ in $\boldsymbol{R_K}$ is composed of the metameric black for the single spectrum $\delta(\lambda_j)$.

$$\begin{aligned} &\boldsymbol{R_K}=[\boldsymbol{B}_1,\boldsymbol{B}_2,\cdots,\boldsymbol{B}_j\cdots\boldsymbol{B}_n]^{t} \\ &\boldsymbol{B}_j^{\,t}=\boldsymbol{R_K}\delta(\lambda_j),\ \delta(\lambda_j)=[0\cdots0,1,0\cdots0]^{t};\ j\text{-th element}=1 \end{aligned} \quad (4)$$

(b) The *j-th* element $B_{65}(\lambda_j)$ in $\boldsymbol{B_{65}}$ is given by the inner product of row vector $\boldsymbol{B}_j$ and input $\boldsymbol{C_{65}}$ as

$$\begin{aligned} &\boldsymbol{B}_{65}=\boldsymbol{R_K}\boldsymbol{C_{65}}=[B_{65}(\lambda_1),B_{65}(\lambda_2),\cdots,B_{65}(\lambda_n)]^{t} \\ &B_{65}(\lambda_j)=\langle\boldsymbol{B}_j\bullet\boldsymbol{C_{65}}\rangle=\sum_{k=1}^{n}B_j(\lambda_k)C_{65}(\lambda_k) \end{aligned} \quad (5)$$

Eq. (5) denotes the exact *metameric black* $\boldsymbol{B_{65}}$ is sensed by applying a 2-D optical filter with the transmittance $B_j(\lambda_k)$ of $\boldsymbol{R}_K$ to the camera input spectrum $\boldsymbol{C_{65}}$.

Now, taking the scalar summation of the elements in the vector $\boldsymbol{B}_j$ as a weighting coefficient for $\boldsymbol{C_{65}}$, Eq. (5) is simplified decisively as

$$\begin{aligned} &\boldsymbol{B}_{65}\cong\boldsymbol{K}^{t}\boldsymbol{C_{65}},\ \ \boldsymbol{K}=[K(\lambda_1),K(\lambda_2),\cdots,K(\lambda_n)]^{t} \\ &where,\ K(\lambda_j)=\left\{\sum_{k=1}^{n}B_j(\lambda_k)\right\} \end{aligned} \quad (6)$$

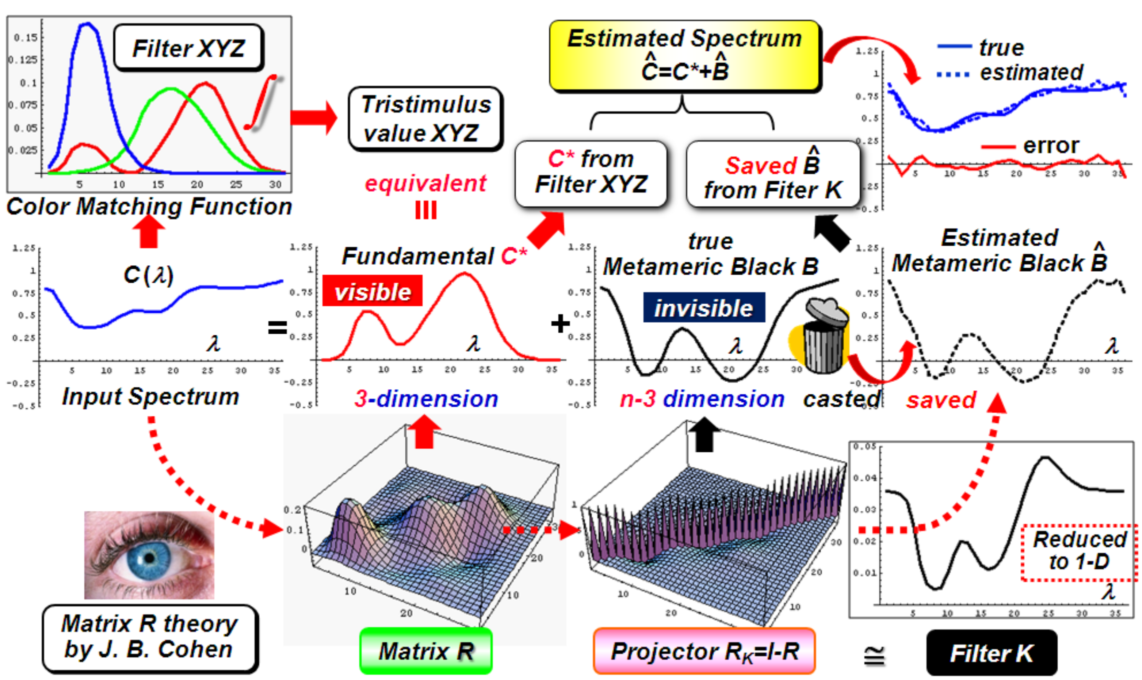

Figure 2 *Why the forth filter should be **K** to save metameric black in compatible with XYZ?*

The vector $\boldsymbol{K}$ represents the transmittance of objective 1-D filter $\boldsymbol{K}$ as a rough approximation for projector $\boldsymbol{R}_K$. Thus the *metameric black* $\boldsymbol{B}_{65}$ is given by a simple product of the 1-D coefficient vector $\boldsymbol{K}$ and the input spectrum $\boldsymbol{C}_{65}$. Geometrically, Eq. (6) means that the $n \times n$ matrix $\boldsymbol{R}_K$ is reduced to $n \times 1$ filter $\boldsymbol{K}$ by the integrated projection along the row (or column) direction. In other words, $\boldsymbol{K}$ is equal to the *metameric black* $\boldsymbol{B}_{EE}$ for the illuminant ***EE*** with *Equal-Energy Spectral Power Distribution*. Indeed, in the case of $\boldsymbol{C}_{65}$=***EE***, Eq. (5) becomes

$$\boldsymbol{B}_{EE} = \boldsymbol{R}_K \boldsymbol{EE} = \boldsymbol{K} \tag{7}$$

Because ***EE*** includes all single spectra equally, $\boldsymbol{K} = \boldsymbol{B}_{EE}$ reflects all of the *metameric black*s corresponding to the entire single spectra. In short, the filter $\boldsymbol{K}$ is simply interpreted to pick up the *metameric black*s of single spectra weighted by the input spectrum $\boldsymbol{C}_{65}$ as given in Eq. (6).

Fig.3 illustrates the geometric structure of 1-D filter $\boldsymbol{K}$ how it's related to the *metameric black* $\boldsymbol{B}_{EE}$ and formed as the integrated projection of $\boldsymbol{R}_K$ to the row (or column) direction.

However, since the *metameric black* $\boldsymbol{B}_{EE}$ has partly negative responses, we can't realize it as a physical filter $\boldsymbol{K}$. The transmittance of optical filter $\boldsymbol{K}$ should satisfy positivity in all ranges.

Assuming the spectral sensitivities of *X, Y, Z, and* $\boldsymbol{K}$ filter are linear independent, the forth filter $\boldsymbol{K}$ may be composed by a linear transform of them without changing any basic property.

Letting the spectral response be $B_{EE}(\lambda)$ for the *metameric black* $\boldsymbol{B}_{EE}$, for example, we can design the spectral sensitivity of forth filter $\boldsymbol{K}$ with positivity by simply subtracting the minimum bias as a constant level as

$$K(\lambda) = B_{EE}(\lambda) - min[B_{EE}(\lambda)] \geq 0 \;\; for\; \lambda = 380nm \sim 730nm \tag{8}$$

Otherwise, by a linear combination with CIE $\bar{x}(\lambda)$ of filter *X* as

$$K(\lambda) = B_{EE}(\lambda) + \bar{x}(\lambda) > 0 \tag{9}$$

Thus, a novel four-band *XYZ*+$\boldsymbol{K}$ filter set with the spectral sensitivity $\boldsymbol{S}$ is formed as

$$\boldsymbol{S} = [\bar{x}(\lambda), \bar{y}(\lambda), \bar{z}(\lambda), K(\lambda)]^t \tag{10}$$

Fig.4 illustrates the normalized spectral sensitivities of *XYZ*+$\boldsymbol{K}$ filter set in case of Eq. (9)

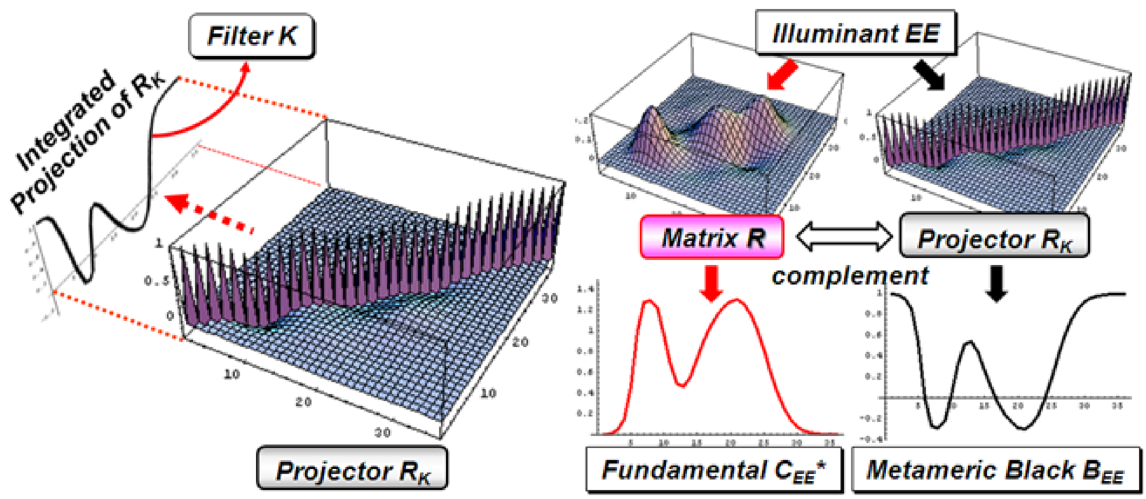

Figure 3 *Basic profile of Filter* ***K*** *approximated by integrated projection to 1-D from 2-D* $\boldsymbol{R}_K$

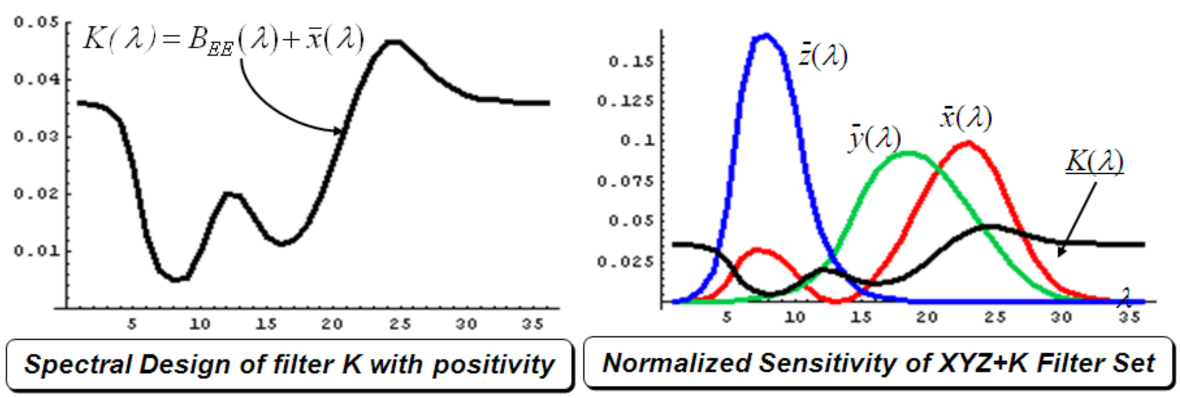

Figure 4 *Spectral sensitivities of filter* ***K*** *and normalized XYZK filter set*

Spectral Estimation from *XYZK* Signal

The optoelectronic signal $\boldsymbol{Q}$ from $XYZ+\boldsymbol{K}$ filter set is given by

$$\boldsymbol{Q}=[X,Y,Z,K]^t=\boldsymbol{S}^t\boldsymbol{C}_{65}+\boldsymbol{e};\ \boldsymbol{e}=system\,noise \quad (11)$$

In order to estimate the input spectrum $\boldsymbol{C}_{65}$ from the four-band signal $\boldsymbol{Q}$, the typical estimation algorithms are applied to the proposed model and its performance was evaluated as follows.

Pseudo-inverse Solution

Neglecting the noise $\boldsymbol{e}$, a solution to minimize the norm (energy) of $\boldsymbol{C}_{65}$ is simply given by applying the well-known pseudo-inverse matrix $\boldsymbol{S}_{inv}$ as

$$\begin{aligned}&\hat{\boldsymbol{C}}_{65}=\boldsymbol{S}_{inv}\boldsymbol{Q},\ \ \boldsymbol{S}_{inv}=\boldsymbol{S}\left(\boldsymbol{S}^t\boldsymbol{S}\right)^{-1}\\&for\ minimizing\ \ \left\|\hat{\boldsymbol{C}}_{65}\right\|=\left(\hat{\boldsymbol{C}}_{65}{}^t\hat{\boldsymbol{C}}_{65}\right)^{1/2}\end{aligned} \quad (12)$$

This is easy to calculate without any a priori knowledge, but isn't always a stable solution.

Smoothed-inverse Solution

Since the color objects in nature have the gentle and smoothed spectral shapes, minimum-norm estimation with the constrained smoothness provides the better solution.
Taking the second derivative of spectral input $\boldsymbol{C}_{65}$ by applying the *Laplacian* operator $\boldsymbol{D}$

$$\boldsymbol{\delta}=\begin{bmatrix}\delta_1\\\delta_2\\\vdots\\\delta_{n-2}\end{bmatrix}=\begin{bmatrix}1\text{-}2\ \ 1\ \ 0\ \ 0\cdots0\\0\ \ 1\text{-}2\ \ 1\ \ 0\cdots0\\\vdots\qquad\ddots\qquad\vdots\\0\cdots\cdots0\ \ 1\text{-}2\ \ 1\end{bmatrix}\begin{bmatrix}C_{65}(\lambda_1)\\C_{65}(\lambda_2)\\\vdots\\C_{65}(\lambda_n)\end{bmatrix}=\boldsymbol{D}\boldsymbol{C}_{65} \quad (13)$$

Because $\boldsymbol{\delta}$ reflects "*edge*" component, its quadratic norm will be a smoothness measure as

$$\begin{aligned}&\boldsymbol{\delta}^t\boldsymbol{\delta}=\sum_{i=1}^{n-2}\delta_i^2=\boldsymbol{C}_{65}{}^t\boldsymbol{D}^t\boldsymbol{D}\boldsymbol{C}_{65}=\boldsymbol{C}_{65}{}^t\boldsymbol{N}\boldsymbol{C}_{65}=\left\|\boldsymbol{C}_{65}\right\|_N{}^2\\&\quad where,\ \ \boldsymbol{N}=\boldsymbol{D}^t\boldsymbol{D}\end{aligned} \quad (14)$$

Now introducing *Lagrange* multiplier $\boldsymbol{\Lambda}$ to minimize Eq. (14) under the smoothing matrix $\boldsymbol{N}$,

$$J(\boldsymbol{C}_{65})=\boldsymbol{C}_{65}{}^t\boldsymbol{N}\boldsymbol{C}_{65}+\boldsymbol{\Lambda}^t\left(\boldsymbol{S}^t\boldsymbol{C}_{65}-\boldsymbol{Q}\right) \quad (15)$$

The scalar term $J(\boldsymbol{C}_{65})$ is minimized when its first derivative is zero

$$\partial J(\boldsymbol{C}_{65})/\partial\boldsymbol{C}_{65}=2\boldsymbol{N}\boldsymbol{C}_{65}+\boldsymbol{S}\boldsymbol{\Lambda}=0 \quad (16)$$

Solving Eq. (16) under Eq. (11), we get the solution by modifying $\boldsymbol{N}$ to be non-singular as

$$\begin{aligned}&\hat{\boldsymbol{C}}_{65}\cong\boldsymbol{S}_m\boldsymbol{Q},\ \boldsymbol{S}_m=\boldsymbol{N}^{-1}\boldsymbol{S}(\boldsymbol{S}^t\boldsymbol{N}^{-1}\boldsymbol{S})^{-1}\\&\qquad\qquad for\ \boldsymbol{N}=\boldsymbol{N}+\varepsilon\boldsymbol{I}\,(\varepsilon<<1)\end{aligned} \quad (17)$$

Wiener-inverse Solution

Wiener-inverse is a popular estimator to minimize *MSE* under the known statistics for signal and noise as follows.
The bias term $\boldsymbol{b}$ is usually ignored as small, but here $\boldsymbol{m}_C\cong0.3$ is used for general case[13].

$$\begin{aligned}&\hat{\boldsymbol{C}}_{65}\cong\boldsymbol{W}_{inv}\boldsymbol{Q}+\boldsymbol{b}\\&where,\ \boldsymbol{W}_{inv}=\boldsymbol{R}_{CC}\boldsymbol{S}\left(\boldsymbol{S}^t\boldsymbol{R}_{CC}\boldsymbol{S}+\boldsymbol{R}_{ee}\right)^{-1}\\&\boldsymbol{R}_{CC}=covariance\ matrix,\ \boldsymbol{R}_{ee}=noise\ variance\\&\boldsymbol{b}=\boldsymbol{m}_C-\boldsymbol{W}_{inv}\boldsymbol{S}^t\boldsymbol{m}_C\\&\boldsymbol{m}_C=mean\ vector\ of\ input\ spectra\end{aligned} \quad (18)$$

Though the true covariance matrix $\boldsymbol{R}_{CC}$ is obtained from trained samples, the Markov model is useful for non-parametric Wiener estimation. Assuming a strong correlation with coefficient ρ between the adjacent spectral components, the covariance matrix $\boldsymbol{R}_{CC}$ is modeled by

$$\boldsymbol{R}_{CC}=\begin{bmatrix}1\ \ \rho\ \ \rho^2\cdots\cdots\cdots\rho^{n-1}\\\rho\ \ 1\ \ \rho\ \ \rho^2\cdots\cdots\rho^{n-2}\\\rho^2\ \rho\ \ 1\ \ \rho\cdots\cdots\cdots\vdots\\\vdots\qquad\qquad\ddots\\\rho^{n-1}\rho^{n-2}\cdots\cdots\cdots\cdots1\end{bmatrix} \quad (19)$$

Finally, removing the illuminant $\boldsymbol{D}_{65}$ from $\hat{\boldsymbol{C}}_{65}$, the spectral reflectance $\hat{\boldsymbol{r}}$ is calculated by

$$\hat{\boldsymbol{r}}\cong diag[\boldsymbol{D}_{65}]^{-1}\hat{\boldsymbol{C}}_{65},\ \boldsymbol{D}_{65}=[D_{65}(\lambda_1),D_{65}(\lambda_2),\cdots,D_{65}(\lambda_n)]^t \quad (20)$$

Experimental Results

Spectral Reflectance Estimation for Color Chips

The proposed model was tested for the spectral recovery of the typical color chips;
(A) Macbeth chart, (B) IT8 chart, (C) Inkjet chip,
(D) Acrylic paint chip in SOCS database
The estimation accuracy depends on the performance of inverse-projection operator from the low-dimensional signal $\boldsymbol{Q}$ (n=4) to the high-dimensional spectrum (n=36). The parametric Wiener-inverse operator is fitted to the trained color samples, while the capability of non- parametric operator depends on how it can well imitate the parametric one without training. Fig.5 shows some examples of inverse-projection operator and the covariance matrix $\boldsymbol{R}_{CC}$.

Fig.6 illustrates a result in the spectral reflectance estimation for #125 chip (skin color) in IT8 and #24 acrylic paint chip (permanent green light) in SOCS. The performance was improved from left to right, resulting best in parametric Wiener-inverse method for all of tested chips.

Spectral Estimation Error

Table1 summarizes the spectral estimation errors. The goodness of the *XYZK* filter will be measured by to what extent the Wiener-inverse reaches SVD, because SVD will be ideal for describing the target by the best-fit eigen functions under the limited order of freedom. The parametric Wiener-inverse (shadowed lists with asterisk mean trained by own chip) resulted in the best and its *MSE* reached nearly to the same level as 4-th order SVD.

This tells the proposed *XYZK* filter is designed reasonably and works excellent in spite of only four bands.

Table2 shows CIELAB ΔE_{ab}* under the changing viewing illuminants. The *XYZK* model clearly shows the error smaller than SVD, even if using the non-trained Wiener. It's a great advantage superior to SVD due to the compatibility with *XYZ*.

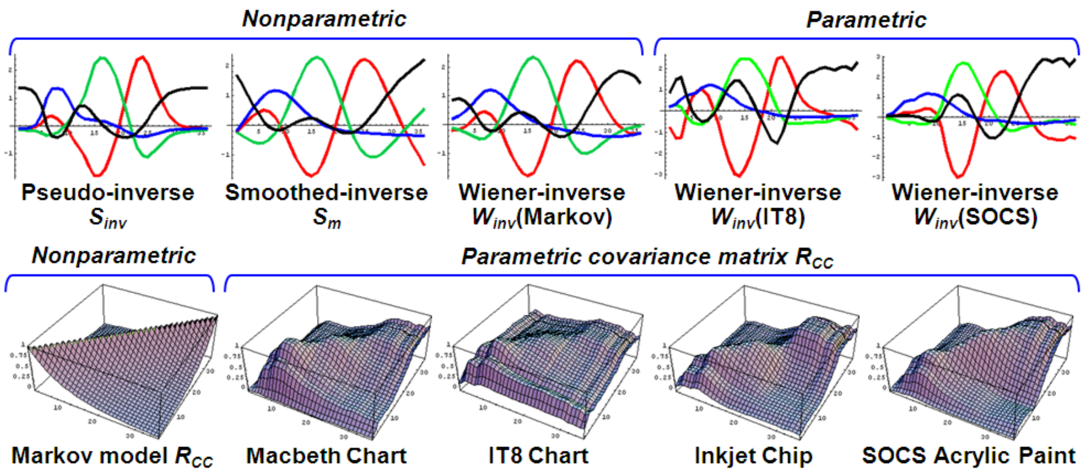

Figure 5 *Spectral estimation operators* (*upper*) *and covariance matrices* (*lower*)

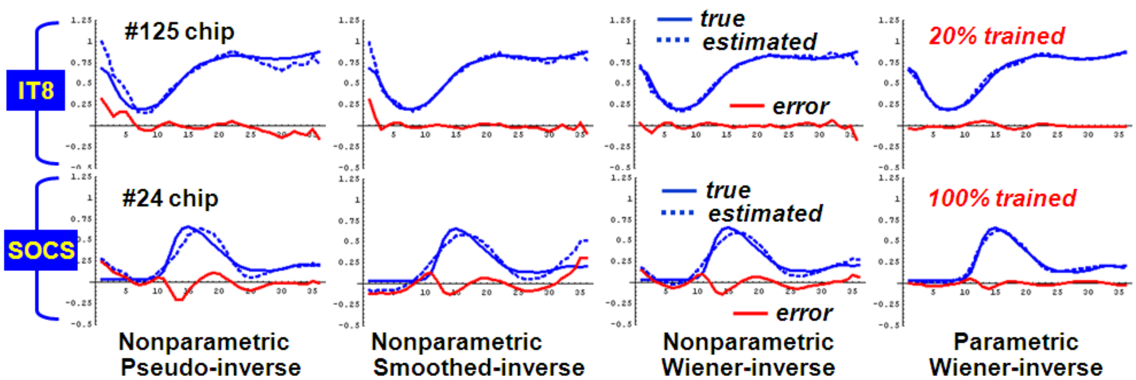

Figure 6 *Example of spectral reflectance estimated by parametric/nonparametric typical models*

Spectral Imaging under different Illuminations

Finally, the spectral image rendition was tested under the different illuminants. Here the pseudo-spectral test images[14] are generated by embedding the spectral inkjet chip in each pixel of sRGB image taken under $\boldsymbol{D_{65}}$. The spectral chip matched to the pixel with minimum $\Delta E_{ab}*$ is picked up from the inkjet spectral palettes, each composed of n=36 bands ($\Delta\lambda$=10 nm). Fig.7 shows the images recovered from *XYZK* signal $\boldsymbol{Q}$ by non-trained Wiener-inverse. It looks just the same as true original when viewed under the same illuminant $\boldsymbol{D_{65}}$. The color changes under the other illuminants are also reflected to the colorimetric color reproduction with color differences less than those by SVD.

Conclusions

A novel *XYZ+K* four-band spectral sensing model is proposed. Based on matrix-*R* theory, the additional filter *K* is designed to save the *metameric black* lost by *XYZ* filter. The model worked nice in the parametric *Wiener-inverse* spectral estimation. Its accuracy almost reached SVD as an ideal model. Though the non-trained *Wiener-inverse* is surely worse than that of trained, it resulted in the colorimetric reproduction superior to SVD. The spectral image restoration is simulated under different illuminants with pseudo-spectral test images that the n=36-band inkjet spectral chip is embedded in each pixel and the model worked successfully.

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Author Biography

Hiroaki Kotera *joined Matsushita Electric Industrial Co., in 1963. He received Doctorate from Univ. of Tokyo. After worked in image processing at Matsushita Res. Inst. Tokyo during 1973-1996, he was a professor at Dept. Information and Image Sciences, Chiba University until his retirement in 2006. He received 1993 journal award from IS&T, 1995 Johann Gutenberg prize from SID, 2005 Chester Sall award from IEEE, 2006 journal award from ISJ and 2008 journal award from SPSTJ. He is a Fellow of IS&T.*

Table 1 Spectral reflectance estimation accuracy in MSE (Mean Square Error)

Estimation Method			Spectral reflectance error (MSE)			
			Macbeth (N=24)	IT8 (N=264)	IJP (N=1331)	SOCS (N=50)
Proposed XYZK Model	Pseudo-inverse		0.108	0.0203	0.106	0.140
	Smoothed-inverse		0.0925	0.0119	0.0696	0.0946
	Non-trained Wiener		0.0790	0.0072	0.0549	0.0693
	Wiener trained by	Macbeth	0.00638*	0.0680	0.0438	0.0123
		IT8	0.0826	0.00207*	0.0541	0.0798
		IJP	0.0382	0.0250	0.0119*	0.0391
		SOCS	0.00841	0.0731	0.0518	0.00939
SVD (4-th order)			0.00626	0.00176	0.00911	0.00907

Table 2 Colorimetric errors in CIELAB ΔE_{ab} (mean) under different illuminants*

Estimation Method	Test chips	Standard Illuminant			Fluorescent Lamp		
		D65	D50	A	Daylight	Cool White	Warm White
Proposed Non-trained Markov Wiener	Macbeth	≲0.1	0.99	3.02	2.19	1.99	3.16
	IT8	≲0.1	0.92	2.28	1.68	2.36	4.43
	InkJet	≲0.1	1.98	6.23	3.31	3.32	6.59
	SOCS	≲0.1	1.78	5.44	2.96	3.57	6.49
Proposed Trained Wiener by each	Macbeth	≲0.1	0.56	1.71	1.06	1.59	2.62
	IT8	≲0.1	0.39	1.07	0.98	1.27	2.03
	InkJet	≲0.1	1.31	4.58	1.98	2.59	4.91
	SOCS	≲0.1	1.17	3.65	2.04	4.07	6.60
SVD (4-th order)	Macbeth	1.77	2.12	2.80	3.28	4.73	3.45
	IT8	2.59	2.56	3.04	4.19	5.32	3.45
	InkJet	5.75	6.00	6.60	7.48	8.50	8.14
	SOCS	5.12	5.75	6.75	7.42	9.27	8.78

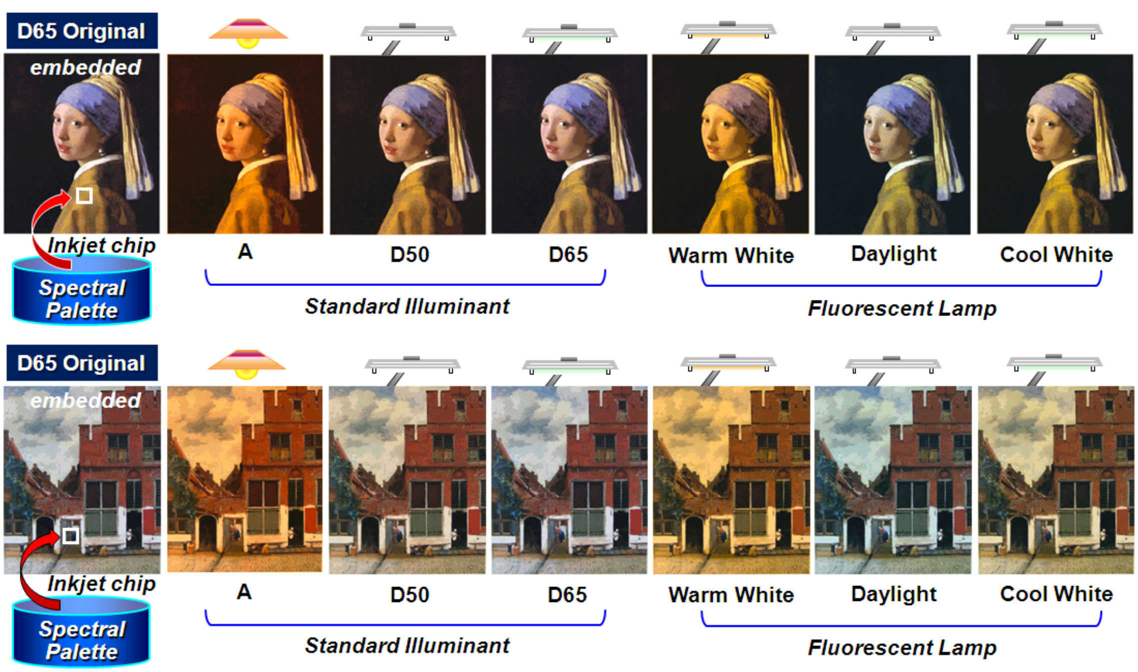

Figure 7 *Colorimetric rendition of spectral image recovered from four-band XYZK low-dimensional signals*