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Spectral band Selection Using a Genetic Algorithm Based Wiener Filter Estimation Method for Reconstruction of Munsell Spectral Data

Keivan Ansari; University of Burgundy, Bat. Mirande, Laboratoire Le2i; Dijon, France.
Department of Color Imaging and Color Image Processing, Institute for Color Science and Technology; Tehran, IRAN.
Jean-Baptiste Thomas; University of Burgundy, Bat. Mirande, Laboratoire Le2i; Dijon, France.
Pierre Gouton; University of Burgundy, Bat. Mirande, Laboratoire Le2i; Dijon, France.

Abstract

Spectrophotometers are the common devices for reflectance measurements. However, there are some drawbacks associated with these devices. Price, sample size and physical state are the main difficulties in applying them for reflectance measurement. Spectral estimation using a set of camera-filters is the eligibly solution for avoiding these difficulties. Meanwhile band selection of filters are needed to be optimized in order to apply in imaging systems.

In the present study, the Genetic algorithm was applied for finding the best set of three to eight filters combinations with specific FWHM. The algorithm tries to minimize the color difference between reconstructed and actual spectral data, assuming a simulation of imaging system. This imaging system is composed of a CMOS sensor, illuminant and 1269 matt Munsell spectral data set as the object. All simulations were done in visible spectrum. The optimized filter selections were modeled on a CMOS sensor in order to spectral reflectance reconstruction.

The results showed no significant improvement after selecting a seven filter set although a descending trend in the color difference errors was obtained with increasing the number of filters.

Introduction

Reconstruction of spectral reflectance of color objects using multispectral imaging is a repeatedly reported challenge in the studies[1-4]. Employing multispectral imaging to the reconstruction of the spectral data relies on the fact that exclusive narrow-band filters can be selected and employed as a spectrophotometer in comparison with broad-band color imaging [5]. Multispectral imaging is the choice for overcoming to the sample area restriction of spectrophotometers and dimensional limitations of three channel cameras [6, 7].

The use of band-pass filters for spectral data measurement was allegedly reported in abridged spectrophotometers that were the first replacement of the colorimeters. These devices truly do the direct measurement of the reflectance data. Responses of this device for each filter were regarded as the reflection at the peak wavelength of the filter. Although this technique was invented to overcome light grating difficulties, it was not as precise as grating spectrophotometers [8]. Therefore, spectral data reconstruction using optical filters would be the replacement of the direct measurement [9].

Optical filters are usually used to increase the spectral resolution or sampling in multi spectral arrays. The accuracy of the spectral data reconstruction strongly relates to the estimation procedure and also to the characteristics of the imaging system including light source, sensor sensitivity and spectral transmission of the filters in the visible range of the spectrum. Although, a naïve solution would be the combinatorial exhaustive search for finding the best answer among all possible filter combinations, it cannot be done in practice [10]. Referring to the statistical well-known formula Eq. (1), assuming r = 8, number of possible combinations, and n = 61 filters peak wavelengths, around three billion combinations should be controlled. It takes long time for an ordinary personal computer to check all these options.

$$C_r^n = \frac{n!}{r!(n-r)!} \tag{1}$$

To reduce the computational time, we applied the Genetic algorithm to overcome such difficulty. The algorithm finds the optimum band position of any desired Gaussian filters. Genetic algorithm is a stochastic general method for solving optimization problems. It uses stimulated mechanisms of biological evaluation systems. In the Genetic algorithm, every possible combination of Gaussian filters as a solution is represented by a chromosome. Then iteration procedure continues with a new population from the current one, until a given ‘‘STOP’’ limit is satisfied or a value of a suitable ‘‘fitness’’ function is reached. The simplest form of Genetic Algorithm involves three types of operators: selection operator; which selects chromosomes in the population, crossover operator which takes two individuals and cuts their chromosome strings at some randomly chosen position for producing two ‘‘heads’’ and ‘‘tails’’ segments and bounds them interchangeably, and mutation operator which is a random process where some of the genes in a chromosome are replaced by another[1, 2].

The response of a CMOS based camera for k^{th} sample at i^{th} color filter, $\mathbf{o}_{i,k}$ $(i=1, 2,\ldots,n_u)$, can be simulated as Eq. (2):

$$\mathbf{o}_{i,k} = \mathbf{S}\mathbf{U}_i\mathbf{E}\mathbf{r}_k \tag{2}$$

Where, n_u is the number of color filters, $\mathbf{U}_i$ is the diagonal matrix of spectral transmittance of the ith color filter, $\mathbf{E}$ is the diagonal matrix of spectral power distribution of an illuminant, $\mathbf{S}$ is the sensitivity of a CMOS, and $\mathbf{r}_k$ is the spectral reflectance of k^{th} sample in the data set. Eq.(2) can be simplified by assuming , $\mathbf{o}_k = \mathbf{F}\mathbf{r}_k$, which, $\mathbf{F}=\mathbf{SUE}$.

Where, $\mathbf{U}=\left[\mathbf{u}_1,\mathbf{u}_2,\ldots,\mathbf{u}_{n_u}\right]^T$ and the superscript T indicates a transposition of a vector or matrix. $\mathbf{E}$ and $\mathbf{S}$ are k ×k diagonal matrices and represent the spectrum of illuminant and the sensitivity of the camera, respectively.

There are many papers focus on use of filters for increasing dimensionality of imaging systems [3-6]. Some papers have used

Gaussian models for simulations of transmission of interference filters. Assuming a function with a definite shape, will reduce the parameters for subsequent optimizations [7]. The Gaussian function is a continuous, symmetric distribution with density function as shown in Eq. (3).

$$u_{\lambda}=\alpha\frac{1}{\sigma\sqrt{2\pi}}e^{-\frac{1}{2}\left(\frac{\lambda_k-\mu}{\sigma}\right)^2} \qquad (3)$$

Where, μ and σ control the center and width of the desired filter.

Wiener filter estimation method [8, 9], is a linear, conventional and well-established method, which can provide an estimation of high dimensional data representation (spectral reflectance) from low-dimensional data representation (camera responses). The reconstruction procedure takes camera responses $\mathbf{o}_k$ as an input, and estimates the output $\hat{\mathbf{r}}_k$ as shown in Eq.(4).

$$\hat{\mathbf{r}}_k=\mathbf{W}\,\mathbf{o}_k \qquad (4)$$

Where $\hat{\mathbf{r}}_k$ shows the estimated spectral reflectance and $\mathbf{W}$ is the Wiener transformation matrix that maps $\mathbf{o}_k$ into $\hat{\mathbf{r}}_k$.

Considering ε_k is the residual error of estimation, it can be written as:

$$\begin{aligned}\varepsilon_k &= \mathbf{r}-\hat{\mathbf{r}}_k\\ &= \mathbf{r}-\mathbf{W}\,\mathbf{o}_k\end{aligned} \qquad (5)$$

The aim of the Wiener filter estimation is to minimize the average squared error distance between the actual and estimated spectral reflectance. Therefore, Eq.(6) can be written as:

$$\begin{aligned}E\left(\varepsilon_k^2\right) &= E\left((\mathbf{r}_k-\mathbf{W}\,\mathbf{o}_k)^T(\mathbf{r}_k-\mathbf{W}\,\mathbf{o}_k)\right)\\ &= E\left(\mathbf{r}_k^T\mathbf{r}_k-\mathbf{r}_k^T\mathbf{W}\mathbf{o}_k-\mathbf{o}_k^T\mathbf{W}^T\mathbf{r}_k+\mathbf{o}_k^T\mathbf{W}^T\,\mathbf{W}\,\mathbf{o}_k\right)\end{aligned} \qquad (6)$$

Where, $E(.)$ is the mathematical expectation function.

The minimum of $E\left(\varepsilon^2\right)$ can be solved when the derivative of $E\left(\varepsilon^2\right)$ with respect to $\mathbf{W}$ is assumed to be zero.

$$\frac{d\left(E\left(\varepsilon^2\right)\right)}{d\,\mathbf{W}}=E\left(-\mathbf{r}_k^T\,\mathbf{o}_k+\mathbf{W}^T\,\mathbf{o}_k^T\,\mathbf{o}_k\right)=0$$

Or

$$-\mathbf{R}_k^T\,\mathbf{O}_k+\mathbf{W}^T\,\mathbf{O}_k^T\,\mathbf{O}_k=\mathbf{0} \qquad (7)$$

The matrix W is calulated as:

$$\mathbf{W}=\mathbf{R}\mathbf{O}^T\left(\mathbf{O}\mathbf{O}^T\right)^{-1} \qquad (8)$$

If replacing $\mathbf{O}$ with $\mathbf{FR}$, $\mathbf{W}$ is calculated as shown in Eq. (9).

$$\mathbf{W}=\mathbf{R}\mathbf{R}^T\,\mathbf{F}^T\left(\mathbf{F}\mathbf{R}\mathbf{R}^T\,\mathbf{F}^T\right)^{-1} \qquad 9)($$

With known $\mathbf{W}$ as Wiener transformation matrix, the spectral reflectance through Eq.(4) is estimated.

Experimental

Imaging system was modeled using Eq. (2). Assuming SNR=100, white, independent, normally distributed noise was added to the system. The generated noise numbers were centered on their mean and then were converted to independent and identically distributed numbers using whitening transformation. Using SNR ratio, a coefficient was calculated to adjust the noise variance. The noise was then added to simulate the multispectral imaging response. The details of contamination of data with noise is fully described in ref [10]. The performance of the method is tested using 1269 matt Munsell spectral reflectance data[11]. All data rearranged between 400nm-700nm with 5nm intervals. Gaussian curves were generated and considered as filters. Full width at half maximum (FWHM) was set at 30 nm. The Gaussian function which simulated transmission of the filters was assumed as shown in Eq. (3) . The sensitivity of a Grass Valley CMOS [12] sensor considered for the simulation of the camera. Standard daylight illumination (D65) was regarded as illuminant.

The mean of ΔE_{2000} was regarded as fitness function for each chromosome in the Genetic algorithm based on wiener filter estimation. Cross over and copy proportion in the optimization procedure were set to 0.6 and 0.2. Moreover, the population size and iteration were adjusted at 100 and 50 respectively.

For comparing the results, the number of filters were changed from 3 up to 8 and the spectrophotometric and colorimetric errors were investigated.

Results and discussion

Figure 1 shows an optimized combination of eight Gaussian filters that are obtained via Genetic algorithm. Fitness function was ΔE2000 between Wiener filter estimation the actual Munsell spectral data.

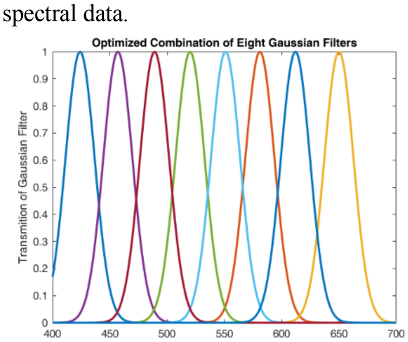

Figure 1: *Selected optimized combination of eight Gaussian filters by Genetic algorithm.*

In figure 2, 1269 actual Munsell spectral data and their reconstructed through the suggested method using 3 and 8 filters are illustrated. In addition, one randomly selected spectral data has been highlighted in the figures. The sample has been redrawn in figure 3 it can clearly be seen that with seven number of filters the more matching occur.

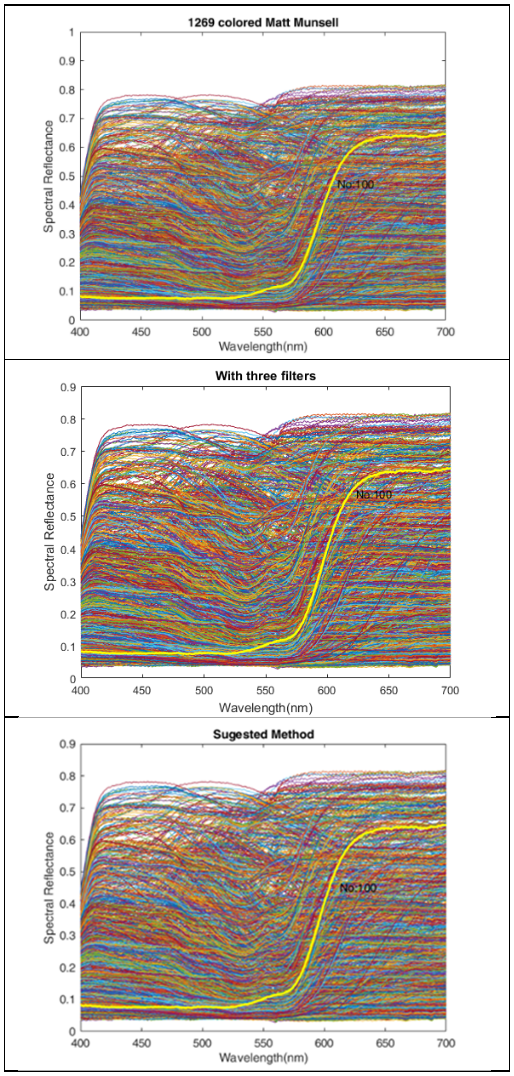

Figure 2: *1269 matt Munsell spectral reflectance data; Actual (above), Suggested Method with 3 filters (middle) and 8 filters (bottom).*

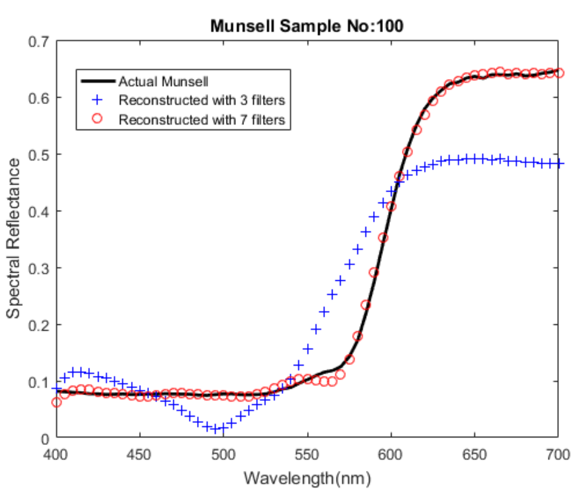

Figure 3: *Spectral data reconstruction of a randomly selected sample (No. 100) through suggested method using 3 and 7 filters.*

In figure 4, the residual estimation errors of 1269 matt Munsell spectral data using 3 to 8 selected filters has been drawn at different wavelengths. Less deviation from zero is obvious in all wavelengths especially in the points which coincide with the transmission peaks of the selected Gaussian filters. Also, the selected peak of bands has been shown at each case in this Figure.

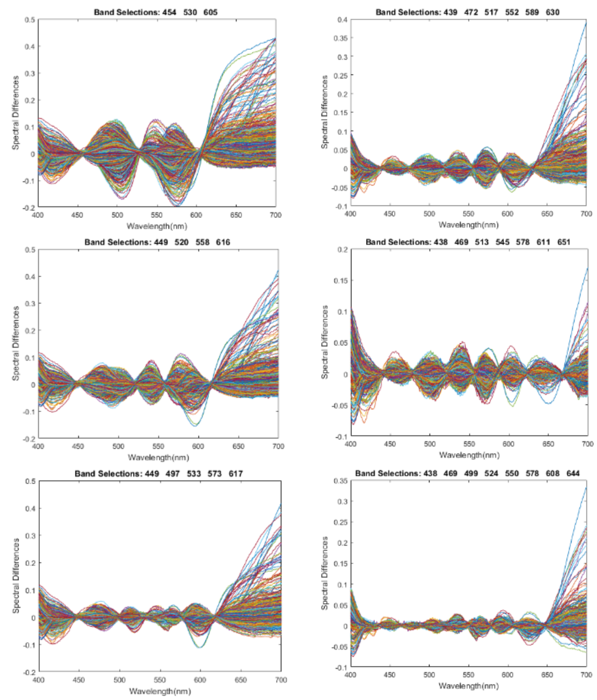

Figure 4*: Residual estimation errors of 1269 matt Munsell spectral data using 3 to 8 selected filters.*

In table 1, the statistical results of RMS and goodness of fitness coefficient (GFC) error metrics of the spectral data is shown. Mean of RMS error for 7 and 8 selected filters exhibit 56 percent improvement in comparison with the 3 selected filters. Moreover, 99% of the reconstructed data using 7 or 8 selected filters have been able to provide a GFC ≥ 0.95 .

Table 1: statistical results between the actual and the estimated 1269 Munsell spectral data with the suggested method using 3 to 8 filters Results

		Numbers of filters					
		3	4	5	6	7	8
RMS	Min	0.0023	0.002	0.002	0.002	0.0019	0.002
	Max	0.1967	0.128	0.1019	0.0955	0.0814	0.0857
	Mean	0.0244	0.017	0.0126	0.0111	0.0091	0.009
GFC	>=0.95	85%	93%	97%	98%	99%	99%
	>=0.99	97%	98%	99%	100	100%	100%

For further investigation, all the spectral data were turned into CIELAB color coordinates under primary and secondary illuminant/standard observer combinations which were D65/2° and F11/2° respectively. Then, the color differences between the actual and the reconstructed data were measured by color difference equation ΔE2000.

Results of table 2 and Figure 5 indicates that the best selection of set of filters is acquired using 7 filters. Although color differences still incline to decrease for 8 filters, the improvement is not significant in practice.

Table 2: ∆E2000 Color differences statistical results between the actual and the estimated 1269 Munsell spectral data with the suggested method using 3 to 8 filters under primary and secondary illuminants.

			Min	Max	Mean	Median	St.D
Numbers of filters	3	D65	0.0205	10.43	1.5908	1.1669	1.4277
		F11	0.0235	8.794	1.4105	0.9845	1.3234
	4	D65	0.0116	3.968	0.4392	0.339	0.4017
		F11	0.0347	4.628	0.9824	0.6534	0.8838
	5	D65	0.0197	3.433	0.2549	0.1921	0.1921
		F11	0.02	5.181	0.5434	0.397	0.5268
	6	D65	0.0038	1.597	0.1032	0.0762	0.0762
		F11	0.0122	5.175	0.6771	0.4401	0.6495
	7	D65	0.0018	0.364	0.0438	0.0355	0.0341
		F11	0.0138	3.201	0.3571	0.2874	0.2874
	8	D65	0.001	0.633	0.0297	0.0249	0.0283
		F11	0.0103	5.269	0.4904	0.3989	0.4169

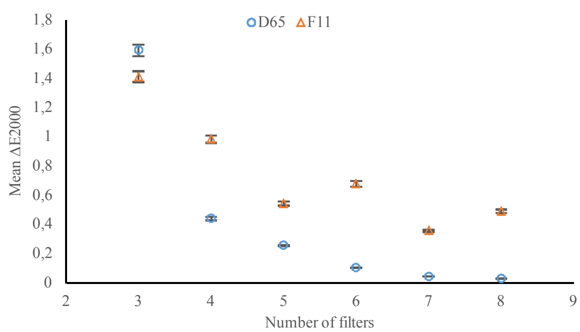

***Figure 5**: Mean and standard error of ∆E2000 Color differences between the actual and the estimated 1269 Munsell spectral data with the suggested method using 3 to 8 filters under primary and secondary illuminants.*

Conclusion

Making use of the Genetic algorithm with fitness function based on Wiener filter estimation error, we obtained an optimized combination of Gaussian filters. Numbers of filters were changed from 3 to 8. Results showed that in multi-spectral imaging, the CMOS sensor can theoretically be equipped with the best optimized selected combination set of filters. Our results indicate that the best set of filters is got using 7 filters. This strategy helps estimating the spectral reflectance of objects.

Regarding the suitable characteristics of CMOS sensors, the research can further be used in near infrared regions as well. Meanwhile, the algorithm may be applied for designing actual Gaussian filters which have the capability to be really designed.

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Author Biography

Keivan Ansari received his PhD in color engineering from Amirkabir University (Polytechnic of Tehran)(2005). Since then he has worked in the Color Imaging & Color Image Processing research group in Color for Siceince & Technology Institute, Tehran, IRAN. His work has focused on the development of Color Physics and its application in Multispectral Imaging.

Jean-Baptiste Thomas received his Bachelor in Applied Physics (2004) and his Master in Optics, Image and Vision (2006), both from University Jean Monnet in France. He received his PhD from University of Bourgogne (2009). He was researcher at the Gjovik University College and at the C2RMF. He is Associate Professor at University of Bourgogne. During 2015-16 he was 50% guest researcher at EPFL. His research focuses on color and multi-spectral imaging.

Professor, Pierre GOUTON. has obtained a PhD in Components, Signals and Systems at the University of Montpellier 2 (France), 1991. He has integrated the Department of Image Processing in the Laboratory of Electronics, Data-processing and Images. Since his main topic research carries on the segmentation of Images by Linear methods or None-linear (mathematical morphology, classification), Color Science, Multispectral Images, Micro and Nano Sensor.