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Novel Adaptive Cellular Yule-Nielson Spectral Neugebauer Color Separation Model for Spectral Image

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Abstract: Considering the problem that huge amount of calculation exists when using Cellular Yule-Nielson Spectral Neugebauer (CYNSN) color separation model for spectral image, the theory that an adaptive-size optimal cell can help to improve the efficiency of CYNSN model is proposed. Based on this theory, on the premise of guaranteeing high precision this study presents an adaptive CYNSN model in which a novel cell-search method is applied. Experiments are properly designed and processed. The experimental results indicate that when the black ink amount value increases, the result can still be in high accuracy if the optimal cell is in a suitably larger size. The adaptive CYNSN model performs well in spectral and colorimetric reproduction, meanwhile elevates the efficiency more than 10 times than other existing CYNSN model.

Key words: Color separation, adaptive CYNSN model, spectral image, cell-search method, high efficiency

INTRODUCTION

In modern image reproduction industry, spectral image technology is widely used because it is in significant character of non-metamerism. Meanwhile, color separation method plays a key role in the process of reproducing the spectral image. It is of importance for a color separation method to work out the recipe of pigments accurately and fast. Cellular Yule-Nielson Spectral Neugebauer (CYNSN), with the characterization of high accuracy, is one of the color separation methods for spectral image. However, the disadvantages of the CYNSN model do exist: firstly, YNSN equation is irreversible when analyzing (Binyu *et al*., 2012); secondly, more importantly, backward CYNSN model (color separation model) can not easily find the cell which the target color is located in.

To solve the first problem, Urban and Grigat (2006) proposed an iterative method based on linear regression to solve the inverse YNSN equation. This method improves the accuracy and efficiency of the inverse YNSN equation. Further more, Urban *et al*. (2007) and Li and Luo (2008) used the 'SV' decomposition and 'QR' decomposition to simplify the matrix manipulation of the above-mentioned method. As to the second problem, Jinyi *et al*. (2010) proposed a cell-searching method: more than 2^K+1(k is the number of primary colors of printer) base-size cells are selected out as possible base-size cells according to the difference in spectral reflectance between target color and imaginary center's color of every base-size cell. In case of CMYK 4-ink printing, at least 17 base-size cells need to be processed every time when predicting optimal recipe of pigments by this way. The amount of calculation turns out to be so huge that it is unlikely to apply this CYNSN model practically.

CYNSN MODEL

For a CMYK 4-ink printing, the classical Yule-Nielson Spectral Neugebauer model can be described as:

$$R(\lambda) = \{\sum_{i=1}^{16} w_i * R_i(\lambda)^{1/n}\}^n \quad (1)$$

where, $R(\lambda)$ is spectral reflectance of given color at wavelength λ; $R_i(\lambda)$ is spectral reflectance of ith primary color at wavelength λ; w_i depends on the C, M, Y, K ink amount values of printed sample which can be described by Demichel equation; n is the coefficient of the power function, known as Yule-Nielson n-factor (Ming *et al*., 2011; Chongchao *et al*., 2011).

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In traditional CYNSN model, the main workflow of backward model is described as follows. First of all, CYNSN model divides printer color space into several base-size cells. Classic Yule-Nielson Spectral Neugebauer model is built in every base-size cell. Secondly, search the optimal base-size cell with the cell-search method. At last, output the recipe of pigments of the optimal base-size cell. The cell-search result in traditional CYNSN model is a base-size cell. With existing cell-search method, the process that recipe of pigments is figured out using reverse YNSN equation and corresponding spectral reflectance are predicted with forward CYNSN model needs to be repeated in several base-size cells before the optimal base-size cell is found. This is exactly why the amount of calculation of traditional CYNSN model is so huge. Generally, on the premise that target color is contained in the cell-search result, the smaller the cell-search result is, the higher precision of the backward CYNSN model is. But, in some subspaces of printer's color space, backward YNSN model built in a larger cell which consists of several base-size cells, already has a comparatively high accuracy. In this case, there is no point subdividing the larger cell. Otherwise, more calculation would be brought in. Based on this theory, an adaptive CYNSN model is proposed in this paper, in which the cell-search result would be an adaptive size cell that includes the target color.

FORWARD ADAPTIVE CYNSN MODEL

The role of forward adaptive CYNSN model is to locate the cell that given color is located in by ink amount values of the given color and to predict the corresponding spectral reflectance. The method of forward adaptive CYNSN model is the same as that of traditional CYNSN model.

Jinyi *et al.* (2010) asserts that forward CYNSN model achieves the optimal predicting precision with the least base-size cells when cell-level is 5. So 5-level CYNSN model is employed in this paper. Training sample set is printed out with six steps of 0, 0.2, 0.4, 0.6, 0.8 and 1 in each of C,M,Y,K color coordinates.

Determine Yule-Nielson n-factor: Generally, Yule-Nielson n-factor is involved in specific experimental environment (printer, ink, paper etc.) and it's hard to work out Yule-Nielson n-factor by a simple mathematical or physical model. Thus, iteration method is introduced to calculate the optimal Yule-Nielson n-factor in this paper. Yule-Nielson n-factor is defined from 1 to 5, 0.3 as interval value. Under all n-factor conditions, spectral reflectance data of testing sample set is predicted with forward model.

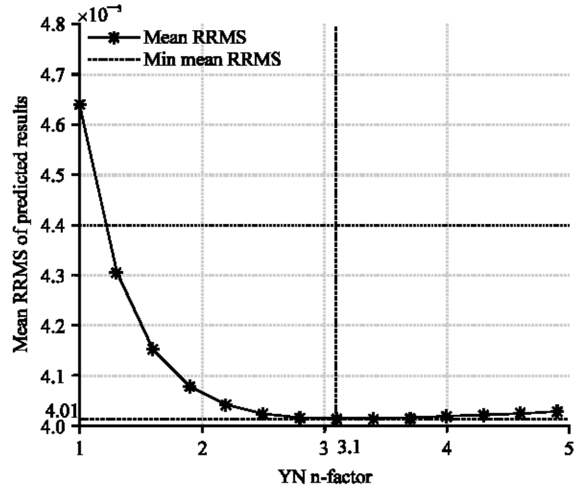

Fig. 1: RRMS error of forward model against n-factor

The optimal Yule-Nielson n-factor is determined by the RRMS error between predicted spectral reflectance and measured spectral reflectance of testing sample set. RRMS can be described by:

$$\mathrm{RRMS} = \sqrt{(R_1 - R_2) * (R_1 - R_2)^T / N} \tag{2}$$

where, R_1 and R_2 are, respectively the predicted and measured spectral reflectance in form of a vector row; T is the matrix transpose operation; N is the dimensionality of spectral reflectance.

As Fig. 1 shows, when n = 3.1, mean RRMS error of forward model, 4.01×10^{-3}, is the minimum value. Thus, in this paper, the optimal Yule-Nielson n-factor is chosen as 3.1.

BACKWARD ADAPTIVE CYNSN MODEL

The proposed adaptive CYNSN model is described in detail by Fig. 2:

Step 1: Determine the position of initial cell based on target spectral reflectance and training sample set's ink amount values data and spectral reflectance data. The initial cell may consist of several base-size cells

Step 2: With the high-accuracy predictive ability of forward model, search the optimal cell inside the initial cell after division. Obtaining the data of optimal cell, like vertexes' spectral reflectance and C, M, Y, K ink amount values and optimal cell's corresponding error

Step 3: Judge if the optimal error is within the acceptable tolerance. If it is, output the optimal C, M, Y, K ink amount values. If not, it means that the initial cell is too small to contain the target color. So, in this case, expand the initial cell and then search the optimal cell again

Search initial cell: In the training sample set, there are some color patches that have the least difference with the target color in terms of spectral reflectance. Pick those out and frame a smallest 4-D cell containing all those picked-out color. Concrete steps are showed in detail as Fig. 3:

Step 1: Calculate the difference D_i ($i = 1, 2, \ldots, n$) between target spectral reflectance $R(\lambda)$ and spectral reflectance of every color patch in the training sample set $R_i(\lambda)$ ($i = 1, 2, \ldots, n$). The difference can be in style of either RRMS or chrominance. In this study, RRMS style is chosen

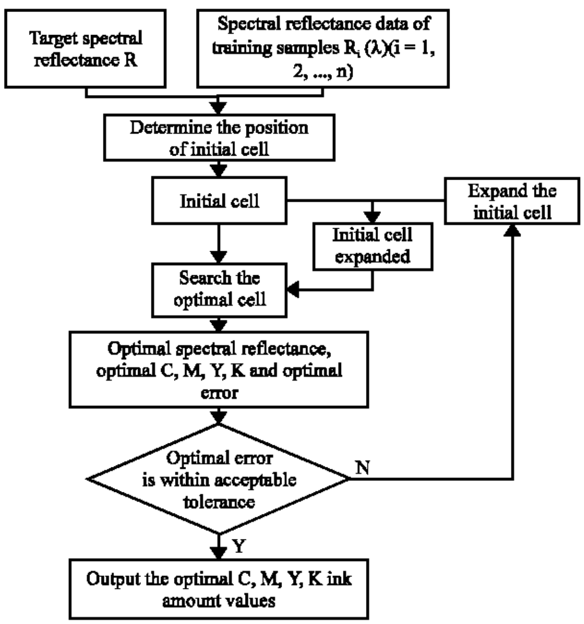

Fig. 2: Specific steps of backward model

Step 2: Sort $R_i(\lambda)$ ($i = 1, 2, \ldots, n$) in the order that D_i ($i = 1, 2, \ldots, n$) ascends, obtaining $R_{si}(\lambda)$ ($i=1,\ldots,n$)

Step 3: Select top j from $R_{si}(\lambda)$ ($i = 1, \ldots, n$), that is $R_{si}(\lambda)$ ($i = 1, \ldots, j$). The initial value of j is set as 2, because at least 2 sets of spectral reflectance data and ink amount values data are needed to frame a cell

Step 4: If a cell can be framed with $R_{si}(\lambda)$ ($i = 1, \ldots, j$), the cell turns out to be the initial cell corresponding to the target spectral reflectance $R(\lambda)$ and the initial cell's position and size can be obtained by its maximum and minimum vertex. If not, add an increment value of 1 to j and repeat the above step 3-4

The steps to judge whether a cell can be framed is described as follows:

Step 1: Find the ink amount values $CMYK_{si}$($i = 1, \ldots, j$) corresponding to $R_{si}(\lambda)$($i = 1, \ldots, j$) from training sample set

Step 2: Figure out the maximum ink amount values of $CMYK_{si}$($i = 1, \ldots, j$) in four ink channels, Cs_max, Ms_max, Ys_max and Ks_max. Similarly, figure out the minimum ink amount values, Cs_min, Ms_min, Ys_min and Ks_min

Step 3: Set Cs_max to 1/grade, if Cs_max equals 0 (grade is the cell-level of the adaptive CYNSN model. In this paper, grade = 5). Then apply the same operation to Ms_max, Ys_max and Ks_max. Similarly, set Cs_min to (grade-1)/grade, if Cs_min equals 1. Then, apply the same operation to Ms_min, Ys_min and Ks_min

Step 4: If (Cs_max-Cs_min)* (Ms_max-Ms_min)* (Ys_max-Ys_min)* (Ks_max-Ks_min) equals 0, the cell can't be framed. If not, it can be framed. Meanwhile, point (Cs_max, Ms_max, Ys_max, Ks_max) and (Cs_min, Ms_min, Ys_min, Ks_min) are the cell's maximum and minimum vertex, respectively. The value of the expression

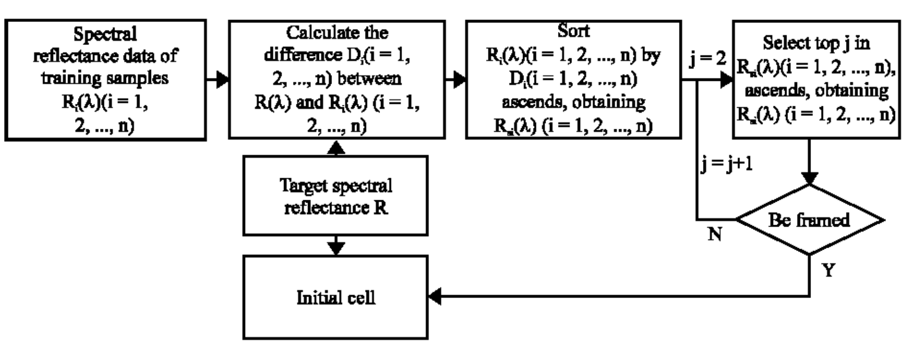

Fig. 3: Specific steps of searching initial cell

(Cs_max-Cs_min)* (Ms_max-Ms_min)* (Ys_max-Ys_min)* (Ks_max-Ks_min) is the size of the cell

Search optimal cell in initial cell: At the beginning of this process, a tolerance for difference between target spectral reflectance and predicted spectral reflectance should be set. In this paper, the tolerance is RRMS<0.00401, taking the mean RRMS error of forward model into account. During the process of searching the optimal cell, if the difference meets the tolerance, it means that optimal cell is found and cell-searching process ends. In this way, accuracy and efficiency of the backward adaptive CYNSN model is well balanced. The complete process is described as follows:

If initial cell is a base-size cell or precision of backward YNSN model in initial cell meets the tolerance, obviously, initial cell is the optimal cell. If not, cut the initial cell into 2 smaller child-cells by a division panel, which is vertical to the axis (C, M, Y or K axis) that the initial cell's maximum span is in and passes through the center point of the initial cell. Select the better performing child-cell and judge whether the precision of the better performing child-cell meets the tolerance. Go on the subdivision with the better performing child cell until the precision meets the tolerance or it becomes a base-size cell.

Expand the initial cell: In practice, it is entirely possible that the initial cell is too small to contain the target spectral reflectance. The possibility leading to that optimal error exceeds the acceptable tolerance. In this paper, the acceptable tolerance is RRMS<0.0193, taking the maximum error of forward model into account. The process is described as follows:

- Go on selecting the top j+1 from $R_{si}(\lambda)(i = 1, \ldots, n)$, mentioned in section 4.1 and judge whether a larger initial cell can be framed by the top j+1. If can be framed, the larger initial cell is the new initial cell. If cannot be framed, j increases 1 and repeat the above process

Iterative method for inverse YNSN equation: In this study, the iterative method mentioned in introduction is used for solving inverse YNSN equation. 'QR' decomposition mentioned in introduction is used to simplify the matrix manipulation.

EXPERIMENTAL RESULTS

The experimental devices and materials used in this paper including:

- **Printing system:** HP Designjet Z3200 12-color inkjet printer
- **Printing material:** EasiColor EP520 210g SemiMatt proofing paper
- **Spectrophotometer:** X-rite i1iO

EFI Colorproof XF software is used to normalize the ink amount values. All sample sets are printed out under this normalization workflow.

Training sample set consists of 1296 color patches as mentioned in section 2.1. Testing sample set which consists of 625 color patches as Fig.4 shows is printed out with five steps of 0, 0.25, 0.5, 0.75, 1 in each of C, M, Y, K color coordinates. Define NO.1-NO.250 color patches of testing sample set as part A, in which K ink amount value is 0 or 0.25. Define NO.251-NO.500 color patches as part B, in which K ink amount value is 0.5 or 0.75. Define the left color patches as part C, in which K ink amount value is 1. Spectral reflectance data is measured in the range of 380-730 nm by spectrophotometer under the condition of (D50, 2°).

Forward adaptive CYNSN model evaluation: Predict the spectral reflectance by ink amount values of testing sample set with the forward model. The difference between predicted and measured spectral reflectance values of testing sample set is analyzed in RRMS, CIELAB color difference ΔE^*_{ab} and ΔE^*_{00} (D50, 2°). The results are summarized in Table 1.

According to the results in Table 1, the forward model is of high accuracy. Thus, the spectral reflectance result predicted by forward model is accurate and credible in the backward model.

Backward adaptive CYNSN model evaluation: Set the measured spectral reflectance of testing sample set as the target spectral reflectance. Predict the C, M, Y, K ink amount values of target spectral reflectance with the backward model. Print out the predicted C, M, Y, K recipe and measure it to get the reproduced spectral reflectance.

Evaluation in precision: The difference between target and reproduced spectral reflectance is evaluated in RRMS error, CIELAB color difference ΔE^*_{ab} and ΔE^*_{00} (D50, 2°; A, 2°; F11, 2°). The results are summarized in Table 2. The backward model performs excellently in spectral reflectance and in chrominance under three different

Table 1: Precision of forward model

	Max	Mean	Median
RRMS	0.0193	0.00401	0.0019
ΔE^*_{ab} (D50, 2°)	2.7400	1.07000	0.8900
ΔE^*_{00} (D50, 2°)	2.3600	0.70000	0.6200

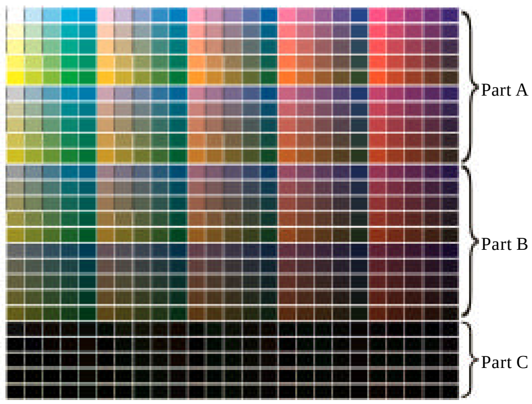

Fig. 4: Printed color patches for testing sample set and the distribution of defined part A, part B and part C

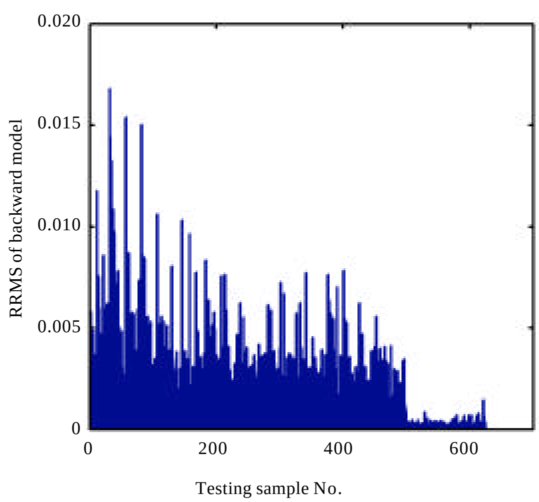

Fig. 5: RRMS of backward model for testing sample set

Table 2: Precision of the backward model

		D50, 2°		A, 2°		F11, 2°	
	RRMS	ΔE^*_{ab}	ΔE^*_{00}	ΔE^*_{ab}	ΔE^*_{00}	ΔE^*_{ab}	ΔE^*_{00}
Mean	0.0031	1.40	0.90	1.40	0.89	1.52	0.94
Max	0.0168	4.72	3.71	5.57	4.42	5.87	4.71
Median	0.0023	1.32	0.85	1.12	0.79	1.33	0.82

luminance conditions. Human vision cannot judge the difference between two images until the image color difference is larger than 2.2 CIELAB units (Chikako *et al*., 2003). So, from the perspective of accuracy for spectral image reproduction, the backward model meets the requirement under different luminance conditions in practice.

Figure 5 shows the RRMS of the backward model corresponding to the testing sample set. In conjunction with Fig. 4, the two diagrams illustrate that the precision of the backward model decreases with K ink amount value increasing.

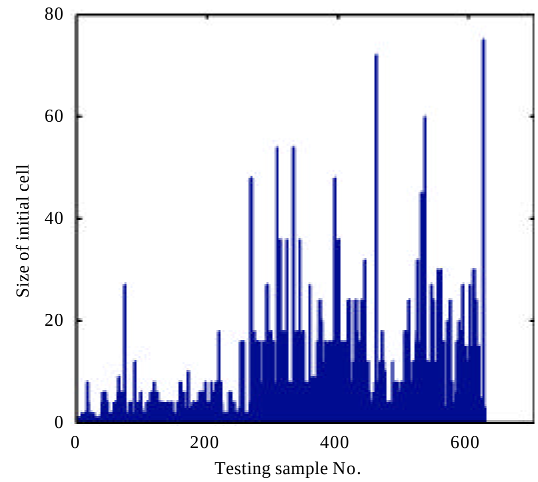

Fig. 6: Size of initial cell for testing sample set

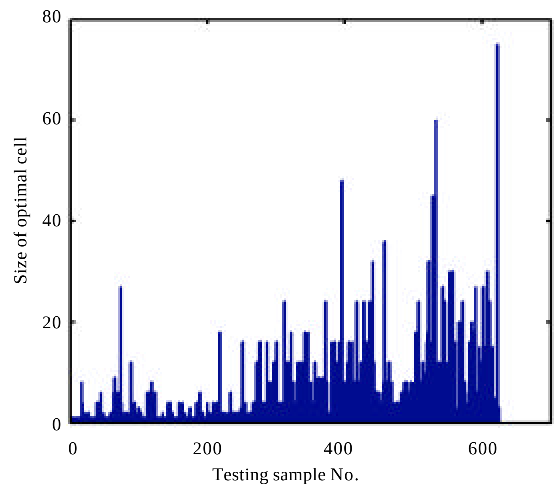

Fig. 7: Size of optimal cell for testing sample set

Evaluation in efficiency: In Fig. 6-8, size of initial cell, size of optimal cell and times of cell calculation are shown by histogram respectively. Once cell calculation includes the both process of figuring out recipe of pigments with reverse YNSN equation and predicting the corresponding spectral reflectance with forward CYNSN model in one cell. The times of cell calculation represents the efficiency of the backward CYNSN model.

In part A, 1.80 times of cell calculation in average is taken to search the optimal cell and the optimal cell is in a

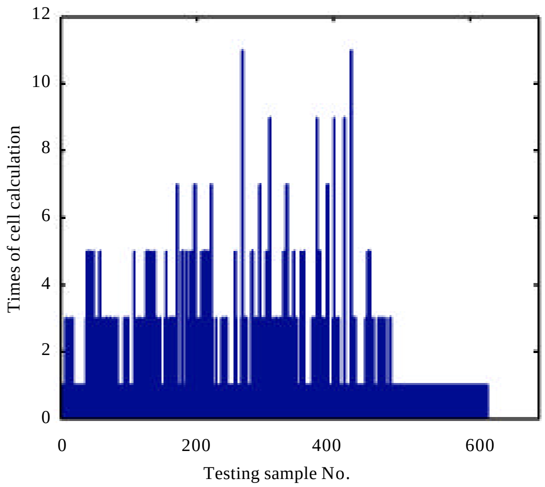

Fig. 8: Times of cell calculation for testing sample set

very small size. Firstly, the initial cell is in a comparatively small size, so less amount of calculation is brought in. Secondly, Size of the optimal cell has a very great influence on the precision. To meet the requirement of accuracy, small-size optimal cell is preferred.

In part B, the case is different. Average 1.89 times of cell calculation is taken to search the optimal cell because backward YNSN equation built in a large cell has a comparatively high accuracy. So, although the initial cell is in a large size, the efficiency of the model is high still. In this part, in order to ensure the efficiency of the backward model, optimal cell can be suitably larger.

In part C, backward YNSN equation built in initial cell already has a comparatively high accuracy because the patches in this part have a great similarity in spectral reflectance. So cell calculation is done almost once.

In summary, the adaptive model has a high efficiency in all three parts. That is 1.67 times of cell calculation for average, which is improved dramatically compared with 17 times by Jinyi *et al.* (2010), are spent. The data and analysis above proves the theory that an adaptive-size optimal cell can balance accuracy and efficiency well.

CONCLUSION

The theory that, on the premise of high precision, an adaptive-size optimal cell can help to improve the efficiency of CYNSN model is proposed. Based on this theory, an adaptive CYNSN model and a novel search-method for the model are presented. The precision and efficiency of the adaptive CYNSN model is analyzed based on the experiment. The results indicate that the proposed color separation model for spectral image performs well not only in spectral and colorimetric reproduction but also in efficiency.

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