Study of Color Rendering Evaluation Method of Light Sources for Printing Matter

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ABSTRACT Based on the optimization of color samples, we have developed a method to evaluate light sources’ color rendering of printing matter. By performing Affinity Propagation (AP) Clustering Algorithm on the color appearance and spectra of the color printing atlas samples printed by a press, two typical color sample sets are obtained. The optimized color sample (OCS) set consists of these two typical color sample sets and it is presented by CMYK dot area coverage. The color rendering indexes (CRIs) CIE-\textit{R}_a, CRI2012, CIE-\textit{R}_f of 90 light sources are calculated by taking the OCS set, color printing atlas and standard color sample (SCS) set of CRI as the test color sample (TCS) set. By comparing the Absolute Difference (AD), Mean Absolute Difference (MAD), Coefficient of Variation (CV) and Spearman Correlation Coefficient (SCC) of the CRIs, we find that the indexes calculated by OCS set are closer to these indexes calculated by color printing atlas than by SCS set. Therefore, the OCS set is more suitable for printing applications. After output from a press and measured spectra, the OCS set with CMYK dot area coverage can be used as the TCS set to evaluate the color rendering of light sources for all printing matter output from this press. For proving the reliability of the results, that is, the universality of the OCS set to the presses, the OCS set with fixed CMYK dot area coverage is output from an another press and CRIs are calculated. The results show that OCS set we developed is better than the SCS set. This method can be used for color rendering evaluation of light sources for printing matter.

INDEX TERMS Color rendering evaluation, typical color sample sets, affinity propagation cluster algorithm, spectral dimension reduction.

I. INTRODUCTION

There are a lot of colors in printing matter around us, so it is meaningful to study the color rendering of lighting source in printing application. CIE-\textit{R}_a and CRI2012’s TCS don’t include printing color samples, while CIE-\textit{R}_f isn’t a specific method for printing color samples [1], [2]. Thus, the existing CRI evaluation method isn’t suitable for printing light sources, especially in special scenes of the enterprise production, such as the subjective assessment of printing quality. Poor color fidelity can cause substantial unwanted color distortion and hence affect critical color judgment [1]. However, there is currently little research related to the specialized applications. Thus, in this paper, we mainly review and study the CRIs. The CRI is commonly used for assessing the color rendering capabilities of artificial light sources. However, some light source with high CRI doesn’t get good color fidelity effect in industrial lighting scene [2]. This is not conducive to the development and advancement of new light sources, that is to say, the high limit of CRI is a major factor in promoting the development and application of the new light source industry [3]–[7].

Limitations of CIE-\textit{R}_a published in CIE 13.3:1995 have been extensively documented, as a result, there were many past efforts to develop complimentary or alternative ways for evaluating light sources’ color rendition [8]–[11]. The CRI2012 metric proposed in 2012 addressed CRI’s criticisms by combining the color appearance space, i.e. CAM02-UCS, with a mathematical reflectance set that exhibited a highly uniform spectral sensitivity [1], [12]. CIE TC1.90 published
a report entitled “CIE 2017 Color Fidelity Index for Accurate Scientific Use” [13], which proposed an updated calculation method for the CRI (renamed color fidelity index (CFI) and abbreviated IES-Ref [14] based on the fidelity index defined by the Illuminating Engineering Society of North America in TM-30-15) and we named it as CIE-R* in this paper.

CIE-R* is based on SCS set’s color difference to evaluate the color fidelity. The other CRIs change the color space and TCS, even improve the calculation formulas to make the evaluation more consistent with human vision. Others also proposed using graphical metric to assess the illumination [15], [16].

The TCS set is undoubtedly considered as a very important dimension [17]. Considering the calculation efficiency of the index, especially for the lamp manufacturers and the independence of large samples due to the limited number of common dyes used to produce them, an ideal sample set would therefore contain only limited samples to reduce computation time, whose spectral features uniformly distributed across wavelength space. In the existing calculation models of CRI, the TCS set is selected according to one or two of the principles of the color appearance distribution uniformity, spectral uniformity, mathematical simulation efficiency, color constancy and metamerism [18].

However, there is less research on the color rendering of light sources in special applications. Existing evaluation methods are not suitable for printing matter lighting scenes since the current TCS set of the color rendering evaluation methods isn’t obtained by the special optimization selection aimed at the printing color samples. Therefore, we focus specifically on the printing application research of such method model. The model is obtained by reducing the number of samples from color printing atlas to the optimal state.

In this paper, section two describes preliminary concepts about color rendering evaluation and reviews the previous relevant research, especially the selection of the TCS set. Section three mainly introduces the overall workflow of the CRI optimization model, the obtainment of data, as well as the theoretical process of clustering. Based on the optimal selection of typical color samples in color printing atlas, a method to evaluate light sources’ color rendering of printing matter is developed. Section four and five focused on the specific clustering process and the optimization model, respectively. Firstly, considering both the color appearance attributes and spectral characteristics of color samples in color printing atlas, AP clustering analysis is used to select two sets of the typical color samples which make up the OCS set. Secondly, by taking OCS set, color printing atlas and SCS set of CRI model as the TCS set, we calculated the CRI (CIE-R*, CRI2012, CIE-Rf) of 90 printing light sources. Thirdly, the CRI calculated by OCS set and the SCS set of CRI models are compared with the one calculated by color printing atlas using three analysis indicators MAD, CV and SCC. In section six, the conclusions are pointed out: for the three indexes CIE-R*, CRI2012 and CIE-Rf calculated by OCS set and SCS set, their MAD, CV and SCC values have consistency. Besides, the CRIs calculated by OCS set are all better than SCS set. In addition, the difference in MAD, CV and SCC between three optimization CRIs is all small, which shows that the OCS set is universal to the CRI models. And taking into account the results of MAD, CV and SCC values, the CRI2012 model with HL17 is the worst and CIE-Rf with OCS set is the best model when evaluating the light sources’ color rendering of printing matter.

For evaluating the light sources’ color rendering of printing matter, the OCS set and CRI model are superior to the existing ones. The OCS set is obtained from color printing atlas and characterized by the dot area coverage of four color CMYK. Therefore, the dot area coverage values of OCS can be taken as fixed sample parameters and generally used for color rendering evaluation of printing light sources.

II. COLOR RENDERING EVALUATION METHODS

In this section, we mainly review three color rendering evaluation indexes CRIs including CIE-R*, CRI2012 and CIE-Rf, focusing on the selection and characteristics of test color samples.

A. THE GENERAL CRI CIE-R*

The CIE-R* is an official evaluation index of light source color rendering in the technical documentation of CIE in 1974. As extensively reported, such a measure has many limitations including the shortage of the selection of the color samples [1]. CRI selected 14 specific colors from the Munsell color system, which induce more sensitivity to some wavelengths than others. The general CIE-R* is obtained by calculating the arithmetic mean of $R_i$ of the first 8 specified color samples which is as shown in formula 1. They have the same brightness and different tones in the CIE1964U* V* W* uniform color space. The last 6 samples which are the saturated color, green leaves and skin color are used to calculate the special color rendering index $R_f$ [11]. In formula 2, $\Delta E_i$ is the color difference of the $i$th sample under the reference source and the test source in CIE1964U* V* W*.

$$R_i = \frac{1}{8} \sum_{i=1}^{8} R_i$$

$$R_f = 100 - 4.6 \Delta E_i$$

B. THE CRI2012

The CRI2012 metric was proposed by Smet et al. in 2012 [1]. Some improvements have been made to CIE-R*. For example, CAT02 chromatic adaptation transformation and CAM02-UCS color space are used. These improvements make experimental data more consistent with human color perception.

It is noteworthy that two new TCS sets named HL17 and Real210 are used. The HL17 is obtained on the basis of mathematical functions and has a minimum change of spectral sensitivity across spectrum. It can avoid gaming and is used for the calculation of the general CRI. The Real210 provides additional information on the expected color shifts when changing illumination. Both of these TCS sets use the set of
100,000 reflectance samples, accumulated by the University of Leeds, as a starting point.

The ideal 1000 wavelength-shifted spectrum set with fine uniform spectral sensitivity is created by using a Monte Carlo approach for generating simulated spectra and adapting the Leeds spectra when generating HL17 set. Then CR2012 designs a set of reflectance spectra with a fairly smooth spectral feature that shifts through the spectrum. Using a series of mathematical methods, the optimization sample set HL17 that emulates the 1000 wavelength-shifted sample set is obtained.

As for the Real210, the 100,000 set is firstly sampled in CAM02-UCS space according to the lightness, chroma and hue. The color difference is set by comparing the color constancy of the metameric samples under different light sources, and then 180 samples are obtained by sampling and filling. Then five representative skin tones of major ethnic groups (African, Caucasian, Hispanic, Oriental and South Asian) are selected four times. In addition, ten reflectance spectra representing typical fine art paint are added as well and the 210 samples are finally obtained.

C. THE COLOR FIDELITY INDEX CIE-R\textsubscript{f}

CIE-R\textsubscript{f} is proposed in the “CIE 224: 2017 CIE 2017 Color Fidelity Index for accurate scientific use” released by the International Commission on Illumination CIE 2017. The CIE- R\textsubscript{f} uses 99 color samples that are spectrally uniform and uniformly distributed in CAM02-UCS. The CIE- R\textsubscript{f} is consistent with IES-R\textsubscript{f} [19].

IES-R\textsubscript{f} selects a large collection of reflectance data as a starting point when filtering the color samples. The resulting Large Set contains about 105,000 reflectance spectra from various types of objects. Firstly, considering the range of validity of color error formulas, IES conservatively chooses the samples in the NCS gamut. Then IES partitions the \((J', a', b')\) color space into cubic pixels and keep only one of the metameric samples in each pixel. The selection procedure yielded a set of real samples that are uniform in color space. Later, IES introduced a flatness figure of merit (F) namely spectral flatness to achieving the spectral uniformity. The Final set containing 99 color samples is built by iterative processing [14], [19].

III. EVALUATION METHOD BASED ON THE OPTIMIZATION OF TCS

A. WORKFLOW OF THE OPTIMIZATION MODEL FOR CALCULATION OF CRI

According to the following postulations and principles, the typical color samples are selected from color printing atlas.

Firstly, it is supposed that the color printing atlas represents most of colors that the press can output. Its color samples could be classified according to the characteristics of color appearance attributes or spectra by AP clustering analysis.

Secondly, for the selected typical color samples, the uniformity of their distribution in color space should be considered. It should yield sufficient accuracy in condition of uniform coverage to all color dimensions (hue, chroma, lightness).

Thirdly, the metric performance could be improved by adopting highly-saturated samples. A light source may exhibit good performance for non-saturated samples while perform poorly with saturated samples, especially for RGB (red-green-blue) white LEDs with strong peaks in their spectra. However, the reverse is found not to be the case. Therefore, we separately select highly-saturated samples at the color gamut boundary of the printing color atlas [8], [20].

Fourthly, considering that the color appearance attributes, metamericism, and the spectral information of the TCS will affect the evaluation results of the color rendering properties, AP clustering analysis is carried out according to the color appearance attributes and spectral characteristics of color atlas to obtain typical color samples and OCS.

Based on the above principles, the overall logical structure and technical route of the optimization model are determined.

The workflow of the CRI optimization model is given in figure 1. It contains two modules, the first one is optimization module and the second one is verification and application module. In the first module, there are five major components:
atlas samples are classified as highly-saturated sample set $\Omega_g$ at the color gamut boundary and the set $\Omega_f$ in the color gamut [17], [20].

3) Obtainment of color printing atlas samples’ color appearance attributes and low dimension spectra by Principal Component Analysis (PCA).

4) Selection of typical color sample sets. AP clustering analysis are carried out for $\Omega_f$ and $\Omega_g$ color samples’ color appearance attributes or low dimension spectra. Their clustering centers are selected as the typical color sample set.

5) Obtainment of OCS set presented by dot area coverage and the CRI calculation model taking the OCS set as TCS set.

The workflow of the optimization module includes five computational steps:

1) The calculation of color appearance attributes and classification of color gamut boundary of color printing atlas samples.

2) Reduction spectral dimension for the color printing atlas samples.

3) AP clustering analysis of the color printing atlas samples according to color appearance attributes and low dimension spectra.

4) Calculation of the CRI $CIE-R_a$, $CRI2012$, $CIE-R_f$ by taking the OCS set as TCS set.

5) Analysis and comparison of the CRI. By calculating the AD, MAD, CV and SCC values of CRI, the optimization performance of OCS set can be shown. If the optimization is not good, it’s needed to re-screen the typical color samples and OCS set. The specific method of judgment and optimization will be described in detail in the next section.

In the verification and application module, there are four major components:

1) Input of the fixed CMYK dot area coverage of the OCS set.

2) Output of the OCS set by any another press.

3) Measurement of the spectral data of the OCS set.

4) Obtainment of the CRI of the printing light sources.

There are two computational steps in the second module:

1) Calculation of CRI of the printing light source which takes the OCS set as the TCS set (application).

2) Comparison of the CRI, if CRI calculated by OCS set is closer to the one by color printing atlas than the existing SCS set of CRI model, that means the fixed OCS set presented by CMYK dot area coverage is effective (verification).

B. THE INTRODUCE AND OBTAINMENT OF COLOR PRINTING ATLAS

Color printing atlas [21] is a color system dedicated to the printing industry. It is usually arranged in the proportion of dots of printing inks of four primary colors: Cyan (C), Magenta (M), Yellow (Y) and Black (K). Color printing atlas gives the color number according to the dot area coverage of the primary colors. For example, label C20M40Y05K0 means 20% dots of blue ink, 40% magenta, 5% yellow, no black, and so on. On each page of the color printing atlas, only two variations of the primary color ink changes in a horizontal direction, and another primary color ink changes in a vertical direction. The other two primary color ink dot values are constant or a few fixed values, and different values are set on different pages, so that the entire CMYK color range can be covered. Among them, the black ink volume of the four-color printing is limited to 80%, and the other three colors can up to 100%.

In practical applications, the greater the number of color samples in the printing atlas is, the more it contributes to the accurate of the color reproduction [22]. Considering the limited number of existing color printing atlas patches, and the difference of the color samples output from different presses, we made our own color printing atlas related to this study.

Firstly, we choose the intervals of dot area coverage which determines the total number of color printing atlas samples. That is, 128,000 color samples at intervals of 5% ((100/5)*100/5)* (100/5)* (80/5) = 128000.

Secondly, the dot area coverage of CMYK is used to characterize the color printing atlas samples and as input parameters to generate the atlas samples. The 128,000 samples with different coverage of CMYK can present all the color output from Epson Stylus 7908 ink-jet press in the matte photo paper.

Thirdly, the atlas samples’ CIE tristimulus values and spectra are measured with the spectrophotometer Eye-One Isis.

C. THE OBTAINMENT OF COLOR APPEARANCE ATTRIBUTES AND CLASSIFICATION OF COLOR SAMPLES

Currently, there are many color appearance models, such as CAM16 and CAM18ls [23]–[25]. Considering the applicability for this article, we choose CAM16 that is simpler than the original CIECAM02 model [26]. For CAM16, the luminance adaptations to the illuminant are completed in the same space rather than in two different spaces, as in the original CIE CAM02 model. Furthermore, its corresponding uniform color space CAM16-UCS is better than CAM02-UCS.

The color appearance attributes $J'$ $a'$ $b'$ of color printing atlas in the CAM16-UCS are obtained under the illumination D65 and the CIE 1931 standard observer function. The distribution of the color atlas samples in CAM16-UCS is basically uniform. When evaluating the color rendering of the light source, the color sample can’t be completely evenly distributed in the color space due to the apparent tolerance. As can be seen from the figure 2, the color atlas meets the requirements [27].

From the color appearance attributes of printing color atlas, we can divide the atlas samples into two parts based on gamut boundary. It is known from the chroma formula that screening boundary saturation samples is mainly done in the plane color gamut $a'$ $b'$. By finding the maximum and minimum yellow-blue $b'$ values corresponding to each $a'$ value in steps of 1, the highly-saturated color sample set $\Omega_g$ at the color gamut boundary and $\Omega_f$ within the color gamut can be classified.
we added contribution coverage as weight to calculate carrying out AP clustering for spectral principal components, which was introduced in section 4.

where two samples, squared is selected as the similarity measure function for any samples, in this paper the negative Euclidean distance is used. The purpose of AP clustering is to produce a similarity clustering model between cluster center without prior knowledge. The core feature of AP clustering is its sole use of responsibility and availability to decide the probability of a point becoming a AP clustering is based on neighbor information propagation [32]. Unlike fuzzy c-means, which computes the mean value of the data points to obtain the centers of the clusters, AP clustering considers all samples as candidates for the cluster center points [33], [34]. And compared with other popular clustering methods, such as k-means [35] and k-medoids [36], [37], which require manual selection of cluster number in advance, the AP clustering automatically locates all the available cluster centers. The core feature of AP clustering is its sole use of responsibility and availability indicators to decide the probability of a point becoming a cluster center without prior knowledge. The purpose of AP clustering is to produce a similarity clustering model between N samples, in this paper the negative Euclidean distance squared is selected as the similarity measure function for any two samples,

\[ S(i, j) = -||x_i - x_j||^2 \]  

(3)

where \( S(i, j) \) is the similarity between \( x_i \) and \( x_j \). When carrying out AP clustering for spectral principal components, we added contribution coverage as weight to calculate \( S \), which was introduced in section 4.

The AP clustering uses the responsibility \( R(i, k) \) and availability \( A(i, k) \) to generate candidate cluster center points. Each iterations of the AP clustering algorithm is the process of alternately updating information between the two parameters \( R(i, k) \) and \( A(i, k) \). Here \( R(i, k) \) is the likelihood of \( k^{th} \) point \( x_k \) to be the cluster center of \( j^{th} \) point \( x_j \), \( A(i, k) \) denotes the suitability of \( x_i \) and \( x_k \) is its cluster center. The detailed calculation steps of the AP clustering algorithm are as follows:

1) Initialize the similarity matrix \( S \) by the similarity between any two samples. Set up the largest number of iterations \( t_{max} \).

2) Calculated \( R(i, k) \) and \( A(i, k) \) of each sample using (4-5).

\[ R(i, k) = S(i, k) - \max_{j \neq k} \{ A(i, j) + S(i, j) \} \]  

(4)

\[ A(i, k) = \min\{0, R(k, k) + \sum_{j \neq k} \max(0, R(i, k))\} \]  

(5)

3) Determine whether the \( k^{th} \) point can be taken as the cluster center point according to (7).

\[ P(k, k) + A(k, k) > 0 \]  

(7)

4) Update \( R(i, k) \) and \( A(i, k) \) of each sample.

\[ R(i + 1, k) = (1 - lam) \cdot R(i, k) + lam \cdot R(i - 1, k) \]  

(8)

\[ A(i + 1, k) = (1 - lam) \cdot A(i, k) + lam \cdot A(i - 1, k) \]  

(9)

Steps (3-4) are utilized to compute the \( R(i, k) \) and \( A(i, k) \) for each sample. Here \( lam \) in (8-9) denotes the damping factor. It is just there for numerical stabilization and can be regarded as a slowly converging learning rate. When updating the messages, it is important to avoid numerical oscillations in some cases. It is advised to choose a damping factor within the range of 0.5 to 1.

5) If \( t \) is greater than the maximum number of iterations \( t_{max} \) or the model reaches the termination condition, terminate the process. Otherwise, go back to step 2.

Figure 3 is an example of an AP clustering result with three cluster centers, in which the horizontal and vertical coordinates represent amplitude and sampling point, respectively.

**IV. AP CLUSTERING ANALYSIS OF COLOR PRINTING ATLAS SAMPLES**

This section describes the process of obtaining two typical color sample sets \( \Theta_1 \) and \( \Theta_2 \) from color printing atlas samples’ color appearance attributes and low-dimensional spectral data by AP clustering analysis. The OCS set consists of \( \Theta_1 \) and \( \Theta_2 \). It is worth reiterating that considering the influence of the highly-saturated color samples on the color printing atlas.
rendering evaluation of the light source, the clustering methods developed in this paper divide the color samples into two parts: TCS set with high saturation at the boundary and the set whose samples are within the bounds of the gamut [20]. The two parts are processed separately with the same process and algorithm.

A. THE TYPICAL COLOR SAMPLE SET $\Theta_1$: AP CLUSTERING OF COLOR APPEARANCE ATTRIBUTES $J'ap'$

As shown in figure 4, for color samples classified into two categories $\Omega_g$ and $\Omega_f$, the AP clustering algorithm is performed directly on the color appearance attributes $J'ap'$ calculated in CAM16-UCS, and each cluster center represents a typical sample. These cluster centers form the typical color set $\Theta_g$ and $\Theta_f$. The typical color sample set $\Theta_1$ includes $\Theta_g$ and $\Theta_f$ which contains 10 highly-saturated typical samples and 45 typical samples within the boundary respectively. In the AP clustering algorithm, when the overall characteristics of the data set are uncertain, it is recommended to set the damping coefficient $\lambda = 0.5$, and the reference degree is the mean of the similarity. It should be noted that in order to ensure the consistency of the methods, the parameter settings in the process of obtaining typical color sample set $\Theta_2$ is the same as set $\Theta_1$.

B. THE TYPICAL COLOR SAMPLE SET $\Theta_2$: AP CLUSTERING OF 6-DIMENSIONAL SPECTRA WITH WEIGHT

In this section, based on PCA introduced in section 3.4, the spectral dimension of color samples within $\Omega_g$ and $\Omega_f$ is reduced from 81 to 6. Each principal component is then multiplied by the corresponding contribution coverage. AP clustering analysis is performed on the products of $\Omega_g$ and $\Omega_f$. Calculating the Euclidean distance when using the contribution rate as the weight can improve the accuracy of the similarity result. That is, the Euclidean distance formula is improved from (10) to (11),

$$ED_i = \Delta p_1^2 + \Delta p_2^2 + \cdots + \Delta p_6^2$$  \hspace{1cm} (10)
$$ED_i = (\alpha_1 \Delta p_1)^2 + (\alpha_2 \Delta p_2)^2 + \cdots + (\alpha_6 \Delta p_6)^2$$  \hspace{1cm} (11)

where $\alpha_i$ is the contribution rate of the $i$th principal component, $\Delta p_i$ is the distance of the $i$th principal component between different samples.

As shown in figure 5, after AP clustering analysis of the 6-dimensional spectra which adding contribution coverage, the typical color samples $\Theta_{g2}$ and $\Theta_{f2}$ obtained from the AP cluster centers are merged into the second typical color sample set $\Theta_2$. In case of color printing atlas, 20 typical color samples within the bounds of the color gamut and 9 highly-saturated samples are obtained.

C. THE OCS SET

The above two methods either consider the chrominance information, or the spectral information. They directly perform AP clustering on the chrominance value or the low-dimensional spectral data. These two algorithms are relatively simple, and the operation speed is relatively fast, but failed to take the phenomenon of metamerism into account. Therefore, the set $\Theta_1$ and $\Theta_2$ form the OCS set $\Theta_{84}$ which contains 19 (10 + 9) highly-saturated typical samples and 65 (45 + 20) typical samples within the boundary. The distribution of these 84 typical color samples $\Theta$ is shown in figure 6.

Within the four quadrants, the numbers of samples are 21, 21, 30 and 12 respectively. Accordingly, the uniformity of
the distribution of samples in the CAM16-UCS color space is well. In the blue area, the number of typical samples is more, which is consistent with the visual capacity.

As shown in Table 1, the color printing atlas is recorded as \( \Omega_{128000} \). The OCS set is represented by \( \Theta_{84} \). And the SCS set of the CRI model is recorded as \( O_i \), where subscript \( i \) represents the number of samples contained in the CRI model. These symbols can describe the sets more simply in subsequent calculation and analysis.

### V. THE OPTIMIZATION COLOR SAMPLE SET AND THE CRI MODEL

In this section, the OCS set are taken as TCS set, and CIE-\( R_8 \), CRI2012 and CIE-\( R_f \) of 90 light sources are calculated. Compared with the SCS set of the CRI model, the optimization performance of our proposed OCS set can be obtained by calculating some metrics. In order to fully analyze the optimization performance, we not only compare the AD, MAD values, but also calculate the CV and SCC values of CRI.

#### A. LIGHT SOURCE

This article uses 90 types of light sources including 3 CIE standard illumination light sources (A, D50, D65), 41 fluorescent light sources [6], 46 LED light sources in the market [38]–[42], and their color temperature ranges from 1717k to 6781K [43], [44]. They are numbered as light source 1, light source 2, light source 3...light source 90 respectively.

#### B. THE CALCULATION OF OCS SET'S PERFORMANCE

A total of 4050 sample data sets are calculated: 3 kinds of CRIs (CIE-\( R_8 \)/CRI2012/CIE-\( R_f \))^* 5 kinds of sample sets (the color printing atlas \( \Omega_{128000} \)+ OCS set \( \Theta_{84} \)+ the SCS set of CRI model (\( O_8 \), \( O_{17} \) and \( O_{99} \))^* 90 light sources =4050.

This shows the procedures and results of the calculation of OCS set’s performance. The color printing atlas is used as reference color sample set \( \Omega_{128000} \). For all light sources, the calculation result of CRI by using the OCS set is closest to the color printing atlas samples, and its MAD, CV and SCC are the best.

The difference between the two sets of data is proportional to the value of AD and MAD. Compared with AD, MAD is absolutely valued due to the dispersion, and there is no positive or negative phase cancellation. Therefore, the MAD can better reflect the actual situation when predicting value error. The calculation formula is shown in (12) and (13).

\[
AD = \left| \frac{CRI^i_k - CRI^{\text{CPA}}_k}{CRI^{\text{CPA}}_k} \right|  \tag{12}
\]

\[
MAD = \frac{1}{n} \sum_{k=1}^{n} \left| \frac{CRI^i_k - CRI^{\text{CPA}}_k}{CRI^{\text{CPA}}_k} \right|  \tag{13}
\]

where \( n \) is the number of the light sources, and \( CRI^i_k \) is the CRI of the \( k \)th light source calculated by taking the OCS set \( \Theta_{84} \) or the SCS set of CRI model \( O_i \) as the TCS set, and \( CRI^{\text{CPA}}_k \) is the CRI of the \( k \)th light source calculated by taking color printing atlas \( \Omega_{128000} \) as the TCS set.

CV is a statistical measure of the dispersion of data points in a data series around the mean. The coefficient of variation represents the ratio of the standard deviation to the mean, and it is a useful statistic for comparing the degree of variation from one data series to another, even if the means are drastically different from one another [45]. The calculation formula is shown in (14) and (15).

\[
CV = \frac{100\%}{\sum_{k=1}^{n} (CRI^i_k - CRI^{\text{CPA}}_k)^2 / (CRI^{\text{CPA}}_k)^2}^{1/2}  \tag{14}
\]

\[
f = \frac{\sum_{k=1}^{n} (CRI^i_k - CRI^{\text{CPA}}_k)^2}{\sum_{k=1}^{n} (CRI^{\text{CPA}}_k)^2}  \tag{15}
\]

where \( n \), \( CRI^i_k \) and \( CRI^{\text{CPA}}_k \) are the same as the one in formula (12), \( CRI^{\text{CPA}}_k \) is the mean values of all light sources’ CRIs calculated by taking the OCS set \( \Theta_{84} \) or the SCS set of CRI model \( O_i \) as the TCS set;

As for SCC, it uses monotonic equations to evaluate the correlation of two statistical variables [46]. The larger the SCC value is, the stronger the correlation between the paired data. The calculation formula is shown in (16),

\[
SCC = \frac{\sum_{k=1}^{n} (CRI^i_k - \bar{CRI}^i)(CRI^{\text{CPA}}_k - \bar{CRI}^{\text{CPA}})}{\left(\sum_{k=1}^{n} (CRI^i_k - \bar{CRI}^i)^2 \right)^{1/2} \left(\sum_{k=1}^{n} (CRI^{\text{CPA}}_k - \bar{CRI}^{\text{CPA}})^2 \right)^{1/2}}  \tag{16}
\]

where \( n \), \( CRI^i_k \), \( CRI^{\text{CPA}}_k \) and \( \bar{CRI}^{\text{CPA}} \) are the same as the one in formula (13), and \( CRI^{\text{CPA}}_k \) is the mean value of all light sources’ CRIs calculated by taking color printing atlas \( \Omega_{128000} \) as the TCS set.

The calculation procedures as follows take CIE-\( R_f \) as an example, and CIE-\( R_8 \) and CRI2012 are the same as it:

1) Using color printing atlas \( \Omega_{128000} \) as the TCS set, \( R_f \) of 90 light sources which is recorded as data set \( R_{1-128000} \) is calculated.

2) Using \( \Theta_{84} \) and \( O_{99} \) as the TCS set, CIE-\( R_f \) is calculated and recorded as \( R_{1-84} \) and \( R_{1-99} \) respectively.

3) Using \( R_{1-128000} \) as reference data, AD, MAD, CV and SCC of \( R_{1-84} \) and \( R_{1-99} \) with \( R_{1-128000} \) are calculated.

4) The OCS set \( \Theta_{84} \) with better MAD, CV and SCC than \( O_i \), that is, the performance of the OCS set is better than \( O_i \) when evaluates the color rendering of printing light sources. The color rendering method which takes \( \Theta_{84} \) as the TCS set is the optimization method.
C. THE RESULTS AND ANALYSIS FOR CIE-RA, CRI2012 and CIE-R1

The calculation results of the AD between Ra-8/84 and Ra-128000 are illustrated in figure 7, and the results of the other two CRIs CRI2012 and RF are illustrated in figure 8 and 9 respectively. The MAD, CV and SCC are shown in table 2. The MAD, CV and SCC calculated with CRI2012 and CRI2012 are illustrated in figure 8 and 9 respectively. The MAD, CV and SCC, of CRIs.

| CRI-Ra | CRI2012 | CIE-Rf |
|--------|---------|--------|
| O8 | O84 | O17 | O84 | O99 | O84 |
| MAD 5.19 | 0.65 | 15.18 | 0.57 | 6.90 | 0.65 |
| CV 6.77 | 1.38 | 10.29 | 0.86 | 3.58 | 0.80 |
| SCC 0.854 | 0.992 | 0.659 | 0.990 | 0.923 | 0.993 |

D. VERIFICATION OF THE PRESS

For proving the universality of the OCS set presented by CMYK dot area coverage to the presses, we randomly select one press to generate the OCS set by inputting the CMYK dot area coverage. The above calculation processes of CRIs by using this OCS set are repeated. The data processing results are as follows.

The MAD, CV and SCC calculated with O84 is better than the SCS set of CRI model, no matter what the CRIs (CIE-Ra, CRI2012 and CIE-R) are. Besides, the result showed by the analytical values is also same as table 2: the best model is CIE- Rf with test color sample set O84. Apparently the OCS set with the smaller MAD and CV, as well as greater SCC is superior to the color sample set O8/17/99 shown in table 3.

VI. CONCLUSION AND DISCUSSION

Based on the optimization of TCS, this paper developed a method for the adaptive color rendering evaluation of the light sources.
sources for printing matter. It is found that the OCS set and its corresponding CRI model outperform the existing CRI models in calculating CRI of light sources.

By inputting the CMYK dot area coverage, 128000 color printing atlas samples are output. Then the spectral reflectance is measured and the color appearance attributes \( J'ab' \) and 6-dimensional spectral information of these samples are calculated. \( J'ab' \) and 6-dimensional spectra data are as raw data to perform AP clustering analysis and we get two kinds of typical color sample sets \( \Theta_1 \) and \( \Theta_2 \). The OCS set contains of \( \Theta_1 \) and \( \Theta_2 \). Set \( \Theta_{84} , O_{8/17/99} \) and \( \Omega_{128000} \) are taken as TCS set to calculate CIE-\( R_a \), CRI2012 and CIE-\( R_f \) of 90 light sources respectively. Compared with the SCS set \( O_1 \), the OCS set whose CRI is closer to the one calculated with \( \Omega_{128000} \) is optimized, so is the CRI model. The degree of optimization is measured by MAD, CV and SCC values indicating that the optimized result is effective. Other press is selected to output the OCS set for verification and the results show that the OCS set \( \Theta \) is better than \( O_{8/17/99} \).

The OCS set is different from the TCS set used in other color rendering evaluation methods. It is expressed in dot area coverage instead of fixed spectral reflectance. Different presses have different optimized color spectra. Such an OCS set is more representative of the color characteristics of the printing matter output from the press. Taking the OCS set output by a press as TCS set of CRI model, the color rendering of the light sources for this printing matter can be better evaluated. It is one of the reasons that the optimization method can be widely used in the evaluation of printing light sources. In a word, the method proposed in this paper is feasible. We can draw the following five conclusions:

1. The effect of OCS set \( \Theta_{84} \) we proposed in evaluating the color rendering of light sources for printing matter is very close to that of color printing atlas. The OCS set with smaller samples reduces the computational complexity and avoids trivial work on the printout of each press.

2. When evaluating the color rendering of the printing light sources, the MAD is an order of magnitude smaller than SCS set of CRI model. \( R_a \)-84/ CRI2012 -84/ \( R_a \)-84’s CV and SCC values are also better than \( R_a \)-8/ CRI2012 -17/ \( R_a \)-99’s, which can effectively shows that our OCS set is better than SCS set in printing application.

3. The difference in MAD, CV and SCC between three optimization CRIs is respectively about 0.1, 0.7 and 0.001, which shows that the OCS set is universal to the CRI models.

4. The best model is CIE- \( R_f \) with test color sample set \( \Theta_{84} \) when evaluating the light sources’ color rendering of printing matter.

5. The spectral reflectance of the OCS set characterized by CMYK dot area coverage varies adaptively with the output of the presses.

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