Estimating color appearance of pearlescent bottles using digital camera

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Pearlescent coatings become highly popular to the modern generation of color rendering materials due to their unique color effect. However, it is quite challenging to evaluate its color appearance by traditional color measurement. A low-cost camera is a highly efficient device for multi-geometry color appearance estimation for pearlescent bottles, which has been achieved through the camera characterization, sample image capturing, and then mathematical transforming from *RGB* (red, green, and blue) values to color appearance attributes based on the color appearance model of CIECAM02. A tele-spectroradiometer for physical measurement together with visual assessment is applied for comparison with the camera method to evaluate the accuracy of camera predictions and discuss the applicability of CIECAM02. The experimental results indicate that the camera data have strong correlation with the physical measurement and also fit well with visual data except for a slight slope shift existing in lightness due to a divinable psychophysical magnitude variation for spatial-dependent color samples. Hence it is feasible to estimate the color appearance of pearlescent bottles using a digital camera.

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For the purpose of business success, the packages like jewellery, cosmetic, or skin-care bottles are usually manufactured with fascinating appearance to attract customers. In recent years, among all the special effect materials exhibiting strong vision impression, the pearlescent pigment has become one of the most popular materials in this field. Pearlescent materials perform high contrasts or lustrous appearances from the flakes in the coating plastics: typically because of the reflection and interference mechanisms of that certain platelets "partially reflect and partially transmit light"[1]. Thus at certain viewing angles, some wavelengths have been strengthened or weakened, such that this special effect is rendered[2,3]. There are numerous researches concerning the color appearance of pearlescent perception, and its gonioapparent property (angle and illuminating dependence) requires more complex considerations if expected to be satisfactorily evaluated for the color appearance. Generally, only one set of colorimetric values is needed to denote a solid color[4], while for pearlescent materials multi-angle or multi-geometry measurement should be conducted[5]. Accordingly, the multi-angle spectrophotometer has been developed for such material measurement that collects the color data from more than one illuminating/viewing angle. Though this scientific instrument is reliable, in some situations it is relatively not affordable and, in addition, factors such as huge sizes (limited portability), low efficiency (human manual operations needed), complexity (only advanced users oriented), and unsystematic (difficulty in merging into the whole industrial application system) are limiting its usage. As a modern imaging system, camera is able to capture a scene in a very short time, which could be considered as a rather robust system for instant obtaining multi-angle colors of pearlescent bottles. This technique is more efficient and economical in online quality control for pearlescent products since it overcomes the related shortcomings of the traditional measurement modes.

An approach for estimating the color appearance of pearlescent bottles using a digital still camera is proposed in this letter. The equipments employed in this experiment include a tele-spectroradiometer (TSR, Konica Minolta CS-1000a), a camera (Nikon D80), a daylight simulator (Gretag Macbeth Spectral Light II Cabinet), a tripod, and a sample-holder box (fixed in the cabinet). The samples are forty-three pearlescent bottles made of masterbatch materials with different base colors produced by Clariant Co., Ltd. This study includes both instrumental and visual methods, aiming to find out how camera method performs according to TSR measurement and visual assessment.

The sample holder was put in the cabinet with the bottles being laid in, which was illuminated by the D65 daylight simulator from the ceiling of the cabinet. According to multi-angle measurement principle, three basic geometries were used approximately in the experiment as illustrated in Fig. 1, i.e., 0/45, 22.5/22.5, and 45/0 denoted as positions 1, 2, and 3, respectively, among which the geometry of 22.5/22.5 was for measuring the specular colors. These three positions of each bottle were measured or assessed for both instrumental and visual approaches. For TSR measurement, manual work was needed to seek appointed points on samples; for camera capture, the Matlab was employed to automatically extract the *RGB* (red, green, and blue) values at relevant locations on bottles in the captured images; and for visual assessment, the psychophysical method of direct ratio, specifically magnitude estimation, was adopted, which was asking an observer to match a number to the perceived magnitude of the attributes under test when the stimulus was presented at each specified positions[6].

The tripod, upon which the camera and TSR were held, was fixed in front of the cabinet throughout the experiment. And the same position was where observers' eyes were laid. Ten observers attended in this experiment, five males and five females, aged between 21 and 26. They were asked to estimate the color appearance magnitude of target points according to the terms of lightness, colorfulness, and hue, with a pair of references corresponding to N10 from Munsell color order system and 3040-R20B from NCS system, which were defined as the lightness of 100 and the colorfulness of 40, respectively. Sequences for visual assessment were randomized to reduce systematic error. In order to quantify the repeatability or reliability of this method, the uncertainties of the camera, TSR, and visual observation were evaluated by measuring or assessing those samples twice, respectively. The correlations of camera and TSR results were estimated for the accuracy evaluation of physical aspect, for the TSR was assumed as the references of physical measurements while the correlations of camera and visual assessment were compared as a result of application of color appearance model in pearlescent material perceptions. The following visual results presented are always the mean values from the ten observers.

The camera, working in manual mode with ISO200, s1/15, F11.0, focus of 35 mm, WB6300K, and resolution of 2896×1944, was characterized by a 20-term polynomial model[4,7,8], in which the RGB values could be transformed to device-independent CIEXYZ specifications. Using Gretag Macbeth Color Checker DC (228 patches) as the training chart and Gretag Macbeth Color Checker (24 patches) as the testing chart, the performance of camera characterization in this experiment was 1.2 (in CIEDE2000 unit) on training data and 1.7 on testing data.

Every set of colorimetric values, or CIEXYZ color specifications, from both TSR and camera were then transformed to lightness (L), colorfulness (C), and hue angle (h, $0°-360°$) through the CIE recommended color appearance model CIECAM02[9−11]. Herewith, the repeatability and accuracy could be depicted in terms of the color appearance attributes L, C, and h, in either instrumental or psychophysical method.

In statistics technique, correlation coefficient (R, the Pearson product moment correlation coefficient) and coefficient of variation (CV)[12,13] are frequently used in color science to investigate how close two sets of data relate with each other. And the coefficient of determination

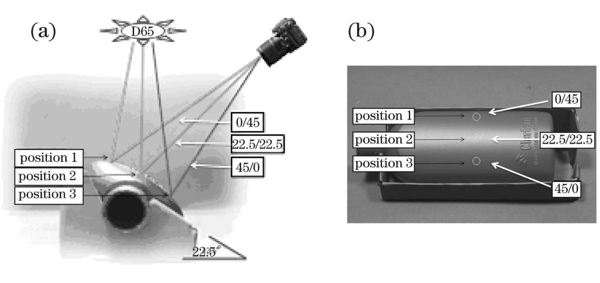

Fig. 1. Experimental placement and its assessed geometries. (a) Experimental geometries from side view; (b) assessed positions from camera view.

(R^2) is considered to be more meaningful than R mathematically. Hereby R^2 and CV are adopted to evaluate the correlations and variations for the measurement data between TSR and camera, as well as between observers and camera.

The correlation coefficient R and coefficient of variation CV are defined as

$$R = \frac{\sum (X_i - \bar{X})(Y_i - \bar{Y})}{\sqrt{\sum (X_i - \bar{X})^2 (Y_i - \bar{Y})^2}} , \quad (1)$$

$$CV = 100\sqrt{\frac{1}{N}\sum_{i=1}^{N}\frac{(X_i - fY_i)^2}{\bar{X}^2}} , \quad (2)$$

where X_i and Y_i ($i = 1, 2, \cdots, N$) represent the two compared data sets, $\bar{X}$ and $\bar{Y}$ denote the mean values of the two data sets, respectively. And the f factor is expressed as

$$f = \frac{\sum_{i=1}^{N} X_i Y_i}{\sum_{i=1}^{N} X_i^2}. \quad (3)$$

R^2=1.000 or CV=0 means perfect agreement between the two arrays of data. For instance, R^2=0.900 and CV=10 indicate 90% agreement, 10% variation, respectively[12].

Table 1 gives the uncertainties in CV as well as R^2 values, calculated for all the iterating works of these three methods. It could be clearly seen that both equipment and psychophysical repeatability were excellent, which set a reasonable baseline for the subsequent procedures. The uncertainty for TSR measurements was slightly poorer than that by camera capturing, which was mainly due to the fact that manual operation was introduced for the former while for the latter the whole system was fixed without any mechanical movement during its whole photographing period. The visual uncertainty was appreciably greater than that in instrumental methods because of the diversification and the non-identity of color sensation from observers. However, the variance of repetitive visual assessment under 10% gave an acceptable result for psychophysical experiment.

The scatter diagrams between the camera predicted and TSR measured values at the three assessed positions of the tested pearlescent bottles are depicted in Fig. 2 for lightness, colorfulness, and hue angle, respectively. The corresponding R^2 and CV values as the correlated performance of the two equipments are listed in Table 2.

The good agreement between the camera acquirement

Table 1. Uncertainties of TSR, Camera Acquirements, and Visual Assessment

Uncertainties	L		C		h	
	R^2	CV	R^2	CV	R^2	CV
TSR	0.970	3.3	0.993	5.0	0.985	5.7
Camera	0.996	1.5	0.997	2.4	0.999	4.0
Observers	0.956	6.0	0.986	7.8	0.963	10.0

and TSR measurement indicated that the camera was competent for effective color appearance estimation instead of TSR. In fact, as a versatile and inexpensive device, the camera has recently been applied in many studies to predict the color appearance of related objects. Martin *et al.* used a camera to measure red wine and achieved the performance as R^2 of 0.90 to 0.99 and CV values of 5.0 to 19.0 with the colorfulness being the poorest predicted among the three color appearance attributes[13]. In the studies by Larraín and León *et al.*[14,15], the color appearances of beef and potato chips were assessed respectively, resulted in R^2 values ranging from 0.58 to 0.99. According to the scatter diagram in Fig. 2, the high-chroma end had larger variations, which was mainly due to the gamut limitation of the camera so that for excessively higher chromatic objects the prediction deviations of camera would likely be enhanced. Furthermore, the performance on position 2 (illuminating/viewing geometry of 22.5/22.5) was a little poorer than other two positions with respect to the correlations due to the specular light demanding much higher dynamic range of the camera as the image capturing device.

The scatter diagrams in Fig. 3 illustrate the results between camera and visual assessment, also in terms of lightness, colorfulness, and hue, whose detailed statistical data are given in Table 3.

All the three attributes have linear relationships. However, colorfulness and hue correlations are better than lightness, and lightness has a conspicuous slope shift (i.e., not perfect agreement) between camera prediction and visual assessment. The CV values can correct such kind of slope variation by the built-in f factor, so that the CV values for lightness seem even more or less the same with colorfulness. The performance of this experiment for instrumental and visual correlations was comparable to the camera method in red wine color appearance measurement (R^2 of 0.80−0.98 and CV of 11.0−21.0)[13]. Additionally, the study with regard to red wine color appearance[13] had the same problem of slope shift in lightness comparisons. It seems that observers would like to tell a narrower range of lightness variation, or they would be accustomed to perceive small psychophysical scale for lightness change, when they were presented a variational object: the color gradient changed with spatial distinctness. As a matter of fact, this theory can be explained from Fig. 4: the left patch pair has L=30 and L=80, respectively, while the right patch has the same lightness at the two ends but uses a gradient change instead of a sharp boundary. Visual perception shows the higher contrast as it is for the left than that for the right. In other words, the psychophysical scale

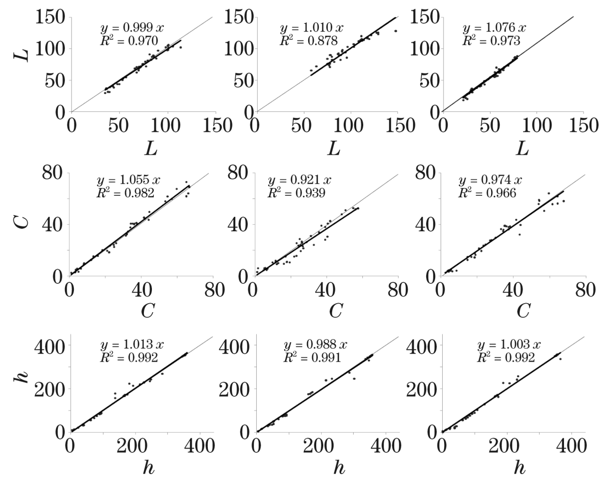

Fig. 2. Scatter diagrams between the camera predicted (abscissa axis) and TSR measured (ordinate axis) values of the tested bottles in terms of the CIECAM02 outputs: lightness (L), colorfulness (C) and hue angle (h). The top, middle, and bottom rows are for comparing L, C, and h, respectively, at the three assessed positions (1−3 from left to right). All the regression lines (solid thick lines) are close to the perfect agreement lines (thin lines).

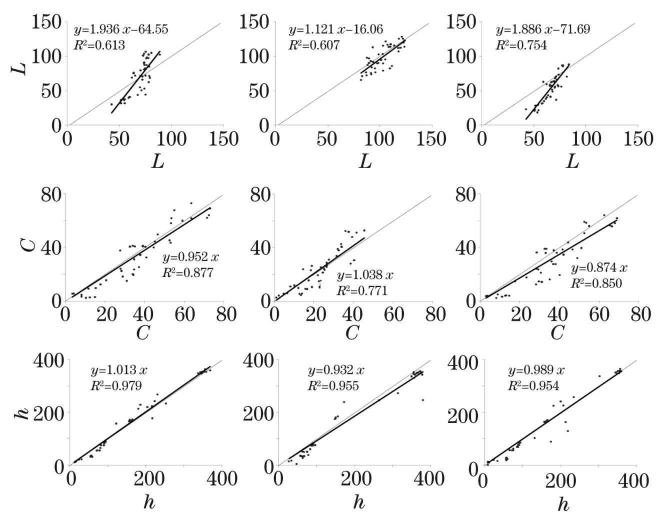

Fig. 3. Scatter diagrams between the camera prediction (ordinate axis) and visual assessment (abscissa axis) of the tested bottles in terms of the CIECAM02 outputs: lightness (L), colorfulness (C), and hue angle (h). The top, middle, and bottom rows are for comparing L, C, and h, respectively, at the three assessed positions (1−3 from left to right). The regression lines (solid thick lines) of C and h are close to the perfect agreement lines (thin lines) while for L attribute the regressions appreciably depart from the perfect agreement lines.

Table 2. Correlations between Camera Acquirement and TSR Measurement in Terms of R^2 and CV

Correlation	L		C		h	
	R^2	CV	R^2	CV	R^2	CV
Position 1	0.970	6.0	0.982	8.3	0.992	6.8
Position 2	0.878	6.2	0.939	15.8	0.991	5.9
Position 3	0.973	5.9	0.966	11.8	0.992	6.4

Table 3. Correlations between Camera Acquirement and Visual Assessment in Terms of R^2 and CV

Correlation	L		C		h	
	R^2	CV	R^2	CV	R^2	CV
Position 1	0.613	25.2	0.877	21.1	0.979	10.6
Position 2	0.607	11.3	0.771	28.7	0.955	14.3
Position 3	0.754	25.5	0.850	23.4	0.954	16.0

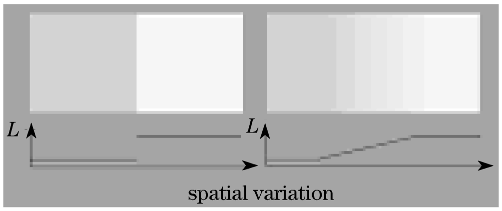

Fig. 4. Spatial change of lightness leads to a different perception scale.

for lightness perception with a spatial change has been cut down. From this view, it would be easy to understand why assessing pearlescent or red wine has slope shift for lightness attribute. CIECAM02 was designed from the experiments based on solid colors, or solid color pairs, just like the left patch in Fig. 4. When viewing spatial-dependent color samples, observers like to give a different but divinable lightness scale, often narrower than usual.

Moreover, from the scatter diagrams it has been seen that the prediction performance of hue angle is the best among the three attributes, while colorfulness is the poorest. Note that hue performance is "colorfulness-dependent". High chroma or saturated colors have better correlations in hue scatter diagram, which could be intuitively illustrated from the scatter diagrams in Figs. 2 and 3. The scatter dots of high chroma targets are distributed along the regression lines (see the bottom row in Fig. 3). If the low-chroma data have been removed, the saturated measured targets would have the CV values of hue between 2 and 4 (corresponding R^2 even greater than 0.999) for camera versus TSR, and CV values around 10.0 (corresponding R^2 greater than 0.967) for camera versus visual result, which implies that, for colored basecoat bottles, this method should be more accurate in hue estimation. Pearlescent materials are rather sensitive to the illuminating and viewing angles, so a slight change of the camera orientation might introduce noticeable deviations, which could be another reason for the systematic error besides the instrumental or visual experiment accuracy.

In conclusion, based on the colorimetric characterization of 20-term polynomial mode, a camera has been adopted for color appearance estimation on angle-dependent pearlescent bottles, with the advantages of low cost, portable and efficient for multi-angle imaging and processing. The experimental results show that the camera predictions closely relate with TSR measurements, as well as with visual assessment data, especially on colorfulness and hue angle correlations based on the existing CIECAM02 color appearance model. It is also revealed that when observing samples with color spatial-dependent property, observers would give a different visual scale for lightness sensation. Additionally, the slight deviation of lightness for the camera method from the visual results would be conquered by slope shift correction on account of their linear relationship preservation. The proposed method would be a promising technique for efficiently assessing the special color appearance of the samples in the future with the increase of commercial usage of pearlescent products. Moreover, the color difference of two pearlescent bottles could be estimated based on their color appearance values. For further industrial applications, more estimating geometries may be necessary, in which case even multi-camera system should be developed in a practical manufacturing environment.

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