A New Parametric Linear Adaptive Color Space and its PCA–based Implementation

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Abstract

In many vision applications, color is an important cue that must be applied very fast. In this paper, after giving a brief review on 12 different standard color spaces, the proposed *parametric linear adaptive color* ($PLAC$) space is defined. A color-based segmentation process is performed on these color spaces. Experimental results show that the $PLAC$ can be applied at least three times faster than the standard color spaces. In addition, with 10% higher distinguishing power, the $PLAC$ shows the fail rate of half as much of the standard spaces. The best advantage of the $PLAC$ is its ability to remove the entire background in 75% of the objects; compared to the low 1.69% of the standard spaces. As the $PLAC$ needs the semiautomatic tuning stage, the proposed $PCA-PLAC$ method is introduced encapsulating the advantages of the $PLAC$ with less required user supervision even than the standard color spaces. The results show the superiority of the proposed color spaces, while the $PCA-PLAC$ even outperforms the $PLAC$.

Keywords: Adaptive color space, principle component analysis, color segmentation, color perceptions, color attributes.

1 Introduction

Color is the way the *human visual system* (HVS) perceives a part of the electromagnetic spectrum approximately between 380^{nm} and 780^{nm}. A color space is a method to *code* a wave in this domain.

1.1 Standard Color Spaces

Although due to practical reasons, RGB color space is widely used in the science and technology, when dealing with natural images it suffers from high correlation between its components: 0.78 for r_{BR}, 0.98 for r_{RG} and 0.94 for r_{GB} [1]. Also the RGB color space has proved to be *psychologically not intuitive* [2] in the way that human has problems imagining pure colors *Red*, *Green* and *Blue* as defined in RGB. Also, RGB is *perceptually non-uniform* [2, 3] because the correlation between the perceived difference of two colors and the Euclidian distance in RGB space is too low.

Different color spaces proposed in the literature with different aims, could be informally categorized into three major categories of HVS-based (including RGB; opponent and phenomenal color spaces), application specific, and CIE color spaces for better understanding [4].

In the late 19^{th} century, *Ewald Hering* proposed the opponent color theory [4]. The relating color space was modelled by different researchers like *Judd*, *Adams*, *Hurvich*, *Jamson* and *Guth* [4], Another One is an excellent color space proposed by *Ohta* [5] as a very good approximation of the *Karhunen-Loeve* transformation of the decorrelated RGB space (The color spaces is sometimes called $I_1I_2I_3$):

$$\begin{cases} I_1 = \frac{1}{3}(R+G+B) \\ I_2 = \frac{1}{2}(R-B) \\ I_3 = \frac{1}{4}(2G-R-B) \end{cases} \tag{1}$$

Phenomenal color spaces, using attributes of *hue* and *saturation* (based on *Newton's color circle*) have been proved to be the most natural way to describe human sense of color [2]. There exists many different color models of this category defined in the literature; such as the HSI (2) [6] and HSV (3) [7] [8]. Although the phenomenal color spaces are very intuitive, but they have inherited the device-dependent tendency from the mother space RGB along with a hue discontinuity around 2π, and the main shortcoming of non-uniform perception.

$$\begin{cases} I = \frac{1}{3}(R+G+B) \\ S = 1 - \frac{min(R,G,B)}{I} \\ H = cos^{-1}\left(\frac{\frac{1}{2}[(R-G)+(R-B)]}{\sqrt{(R-G)^2+(R-B)(G-B)}}\right) \end{cases} \tag{2}$$

$$\begin{cases} V = max(R,G,B) \\ S = \frac{max(R,G,B)-min(R,G,B)}{max(R,G,B)} \\ H = \begin{cases} h, B \leq G \\ 2\pi - h, B > G \end{cases} \\ h = cos^{-1}\left(\frac{\frac{1}{2}[(R-G)+(R-B)]}{\sqrt{(R-G)^2+(R-B)(G-B)}}\right) \end{cases} \tag{3}$$

Application specific color spaces are those invented for special commercial purposes including the spaces used in printing systems ($CMYK$ (4)) [9], television systems (YUV (5) [10], YIQ (6) [11], YC_bC_r (7) [12]) and photo systems (YCC). These color spaces are quite nonintuitive and perceptually non-uniform.

$$\begin{cases} K = min(\tilde{C}, \tilde{M}, \tilde{Y}) \\ C = \frac{\tilde{C}-\tilde{K}}{1-\tilde{K}} \\ M = \frac{\tilde{M}-\tilde{K}}{1-\tilde{K}} \\ Y = \frac{\tilde{Y}-\tilde{K}}{1-\tilde{K}} \\ \tilde{C} = 1-R, \tilde{M} = 1-G, \tilde{Y} = 1-B \end{cases} \tag{4}$$

$$\begin{cases} Y = 0.30R + 0.59G + 0.11B \\ U = -0.15R - 0.29G + 0.44B \\ V = 0.62R - 0.52G - 0.10B \end{cases} \tag{5}$$

$$\begin{cases} Y = 0.30R + 0.59G + 0.11B \\ I = 0.60R - 0.28G - 0.32B \\ Q = 0.21R - 0.52G + 0.31B \end{cases} \tag{6}$$

$$\begin{cases} Y = 0.30R + 0.59G + 0.11B \\ C_b = 0.56(B-Y) \\ C_r = 0.71(R-Y) \end{cases} \tag{7}$$

In 1931, CIE laid down the CIE1931 standard to make a resolution for the device-dependent tender of RGB color space and others spaces based on it. The standard leads to the standard $CIE - XYZ$ as a color space describing the average human observer (8). In 1976, CIE proposed two color spaces named officially as $CIE - Lu^*v^*$ (9) and $CIE - La^*b^*$ (10) whose main goals were to provide a perceptually uniform space, of course later it was proved that the $CIE - Lu^*v^*$ is not entirely uniform [13]. The newly defined color space $CIE - L^*H^oC^*$ (11) is the polar version of the $CIE - La^*b^*$ [9].

$$\begin{cases} X = 0.61R + 0.17G + 0.20B \\ Y = 0.30R + 0.59G + 0.11B \\ Z = 0.00R + 0.07G + 1.12B \end{cases} \tag{8}$$

$$\begin{cases} L^* = 116f(\frac{Y}{Y_0}) \\ u^* = 13L^*(\acute{u} - \acute{u}_{White}) \\ v^* = 13L^*(\acute{v} - \acute{v}_{White}) \\ \acute{u} = \frac{4X}{X+15Y+3Z} \\ \acute{v} = \frac{9Y}{X+15Y+3Z} \end{cases} \tag{9}$$

$$\begin{cases} L^* = 116f(\frac{Y}{Y_0}) \\ a^* = 500(f(\frac{X}{X_0}) - f(\frac{Y}{Y_0})) \\ b^* = 500(f(\frac{Y}{Y_0}) - f(\frac{Z}{Z_0})) \end{cases} \tag{10}$$

$$\begin{cases} L^* = 116f(\frac{Y}{Y_0}) \\ H^o = tan^{-1}\left(\frac{b^*}{a^*}\right) \\ C^* = \sqrt{a^{*2} + b^{*2}} \end{cases} \tag{11}$$

Where $f(x)$ in (9) and (10) and (11) is the function:

$$f(x) = \begin{cases} x^{\frac{1}{3}}, x > 0.008856 \\ 7.787x + \frac{16}{116}, else \end{cases} \tag{12}$$

1.2 Color Image Processing

In many applications of vision , color is an important cue (because it is robust towards changes in orientation and scaling and can well tolerate occlusion), but it is often computationally expensive. For example, the *RoboCup* games are held in a field officially defined as "*a square with green carpets and white walls in which two teams of four or five completely black robots are trying to kick a red ball toward two goals colored in blue and yellow respectively*" [14]. In this atmosphere, vision is the essential tool to recognize objects and is based on the color diversity. For a soccer player robot, going towards the ball at about $2^{m/s}$ velocity, processing 16 frames per second results in about 30^{mm} error in each frame (500^{mm} error in any second.), which is a real shortcoming. This proves the need for an enough accurate algorithm that is performed fast enough.

There are a few color space comparison articles in the literature. A recent work [15] considers the effects of color space selection on the skin detection performance, reporting that non of the 8 color spaces of normalized RGB ($NRGB$ also called NCC), $CIE-XYZ$, $CIE-La^*b^*$, HSI, spherical coordinate transform (SCT), YC_bC_r, YIQ, and YUV seemed to respond better than others. Another paper [16] investigates 5 color spaces including RGB, YIQ, $CIE-La^*b^*$, HSV, and Opponent color, and experimentally compares them in terms of human ability to produce a given color by changing the coordinates in a given color space, the paper does not concern the segmentation.

1.3 Spotting Colors

The first step towards recognizing an object in a captured image is to distinguish it from the background. Although different segmentation methods have been proposed (For two new methods see [17, 18].), but the accuracy and speed of such algorithms greatly depend on the selection of the feature vector describing the color information.

An *object-in-image* segmentation process is meant to detect the area containing the object; and to extract the edges between the object and the background. When using such method, the result may include some parts of other objects. This is sometimes inevitable but for performance reasons, an accurate segmentation task is preferred which completely removes the background.

It must be denoted that segmentation processes, that work on color information of each pixel independent of the neighborhood information are more preferred for their *byte-steam* tender and algorithm speed.

Spotting colors concerns with the accuracy with which objects of a specific single color can be identified in a complex image [19].

Although many color-based object recognition methods has been proposed [20, 21, 22, 23] but generally they work on a multicolored object. For example *Yullie* [22] proposed an algorithm for detecting street signs. The method uses the relative appearance of the two colors in the signs. Algorithms proposed by *Ennesser* [21] and *Funt* [23] uses color-edge histograms for recognizing a multicolored object.

Although many sophisticated methods for color space clustering exist in the literature, but we selected a simple comparison method, assuming that the selected color space is well-defined. A recent work [24] uses 6 marginal values for the three channels but proves that the common comparing operation is not suitable for pipelining; it proposes the use of a lookup table instead and reports the application of such method in a soccer robot with 2^{MB} of RAM. As the method needs a large mass of memory and is slow and tedious when trying to learn another region to the system, we limited the comparison to just one channel, putting emphasize on proper color space selection but making the whole operation faster.

2 Principle Component Analysis

The idea of reducing the color space dimension is not a new idea; many researchers have reported benefits of illumination coordinate rejection (For an example see [15], for further information see [25]).

The principle component analysis (PCA) [26] (For more information see [27, 28].) is widely used in signal processing, statistics, and neural networks. In some areas, it is called the (discrete) *Karhunen-Leove* transform (in continuous case) or the *Hotelling* transform (in discrete case).

The basic idea behind the PCA is to find the components $s_1 \dots s_n$, so that they explain the maximum amount of variance possible by n linearly transformed components. By defining the direction of the first principal component, say w_1, by (13), the PCA can be represented in an intuitive way [26].

$$w_1 = \arg\left(\max_{|w|=1}\left[E\{(w^T x)^2\}\right]\right) \tag{13}$$

Thus, PCA is the projection of the data on the direction in which the variance of the projection is maximized. Having determined the first $k-1$ principal components, w_k is determined as the principal component of the residual stated as [26]:

$$w_k = \arg\left(\max_{|w|=1}\left[E\{(w^T\Delta_{k-1})^2\}\right]\right) \quad (14)$$

Where Δ_{k-1} in (14)is defined as:

$$\Delta_{k-1} = x - \sum_{i=1}^{k-1} {w_i}^T x w_i \quad (15)$$

The principal components are then given by $s_i = w_i^T x$ [26].

In practice, the computation of w_i can be simply accomplished using covariance matrix $C = E\{(x-\bar{x})(x-\bar{x})^T\}$. The w_n is the eigenvector of C corresponding to the n^{th} largest eigenvalue [26].

The basic goal in PCA is to reduce the data dimension. Thus, one usually chooses $n \ll m$. Indeed, it can be proven that the representation given by PCA is an optimal linear dimension reduction technique in the mean-square sense. Such a reduction in dimension has important benefits. First, the computational overhead of the subsequent processing stage is reduced. Second, noise can be reduced, as the data not contained in the n first components may be mostly due to noise [26].

3 Proposed Methods

3.1 Spotting Colors

A simple color spotting task is assumed as discussed in section 1.3 and a new *parametric linear adaptive color* ($PLAC$) space is introduced that performs the task more accurately and more robust compared to 12 standard color spaces. As $PLAC$ needs tedious tuning job, a new *Principle Component Analysis Based Parametric Linear Adaptive Color* $PCA-PLAC$ space is introduced that encapsulates the promising results of $PLAC$ with a tuning method even easier than the standard color spaces'.

3.1.1 Standard color spaces

Although any standard color space is defined as a function $G : R^3 \rightarrow R^3$, in this paper we face each channel of a color space independently. So we are concerned to perform the classification according to a function $X : R^3 \rightarrow R$. In order to comply with notions of (17) and (21), the discrimination function is defined as:

$$f^X_{C,T}(\vec{c}) = \begin{cases} 1, |X(\vec{c}) - C| \leq T \\ 0, else \end{cases} \quad (16)$$

Where $X(\cdot)$ is the function producing one of the channels of a selected color space out of the coordinates of $\vec{c}$ in RGB space.

3.1.2 Parametric Linear Adaptive Color Space

Most of the standard color spaces suffer from the disadvantageous fixed structures that makes them inefficient in treating special odd-shaped loci in the color space. This was the main motivation for defining the *parametric linear adaptive color* ($PLAC$) space formulated in (17) with 5 user-selected parameters a_r, a_g, a_b, C, T.

$$\begin{cases} f^{PLAC}_{a_r,a_g,a_b,C,T}(\vec{c}) = \begin{cases} 1, |\vec{a}^T\vec{c} - \tilde{C}| \leq \tilde{T} \\ 0, else \end{cases} \\ \tilde{C} = \Sigma_{a_x<0} a_x + C\frac{\Sigma|a_x|}{255}, \tilde{T} = T\frac{\Sigma|a_x|}{255} \\ \vec{a} = \begin{pmatrix} a_r & a_g & a_b \end{pmatrix}^T \end{cases} \quad (17)$$

$PLAC$ is a $1-D$ color space; in contrast with the ordinary $3-D$ and $4-D$ color spaces.

3.1.3 Principle Component Analysis-Based Parametric Linear Adaptive Color Space

As the tuning phase of $PLAC$ needs massive user work, a new color space named as *principle component analysis-based parametric linear adaptive color* ($PCA-PLAC$) space is also introduced.

Rather than the numerical parameters tuned by the user in $PLAC$ and other color spaces, $PCA-PLAC$ extracts the information from the scene. When trying to use $PCA-PLAC$, one must give a rectangle of the desired segment to the algorithm (Let's call the region as R.). By forming the $3 \times A$ (A is the area of R) matrix S containing the RGB values of all pixels in R , the vector $\vec{\eta}$ is computed by row averaging of S to give $E_{\vec{c}\in R}\{\vec{c}\}$ as a 3×1 vector. This vector is used to produce the matrix D as the center oriented version of S . The eigenvalues of the matrix $C = D^T D$ are computed and the eigenvector corresponding to the largest eigenvalue is selected to be $\vec{v}$.

The *reconstruction error*(RE) of a point regarding to the region R is defined as (18) in which smaller values shows more tendency. in (18), $\langle\vec{v}\rangle$is a custom norm function defined in (19). The marginal reconstruction error is computed as (20) and a tolerance is asked from the user (λ). The classification function for an arbitrary point is defined in (21).

$$e_R(\vec{c}) = e_{\vec{v},\vec{\eta}}(\vec{c}) = \langle\ \acute{\vec{v}}[\vec{c}-\vec{\eta}]\vec{v} - [\vec{c}-\vec{\eta}]\rangle \quad (18)$$

$$\langle\vec{v}\rangle = \frac{1}{N}\Sigma_{i=1}^{N}|v_i| \quad (19)$$

$$\tilde{e}_R = \arg_{c\in R}\{P(e_R(\vec{c}) < e) > 0.95\} \quad (20)$$

$$f_{R,\lambda}^{PCA-PLAC}(\vec{c}) = \begin{cases} 1, e_R(\vec{c}) \le \lambda\tilde{e}_R \\ 0, else \end{cases} \quad (21)$$

It must be emphasized that although $PCA - PLAC$ needs user to draw a rectangle on the selected object, there is only one user-selected parameter to be tuned in $PCA - PLAC$ in contrast with the 5 parameters in $PLAC$. It is worth mentioning that tuning $PCA - PLAC$ is more intuitive compared to tuning $PLAC$.

To find out the repeatability of $PCA - PLAC$, the correlation between different results of spotting one object was computed as (22), along with a parameter showing the range of the tolerance in different tests on the same object as (23).

$$\delta_{I_1I_2} = 2\frac{\Sigma\Sigma I_{1_{x,y}} I_{2_{x,y}}}{\Sigma\Sigma(I_{1_{x,y}} + I_{2_{x,y}})} \quad (22)$$

$$\tilde{\delta}_\lambda = \frac{\delta_\lambda}{\bar{\lambda}} \quad (23)$$

3.1.4 Comparison Method

The 12 different color spaces under investigation are RGB, $CMYK$, HSI, $I_1I_2I_3$, $CIE - La^*b^*$, $CIE - L^*H^oC^*$, $CIE - Lu^*v^*$, $CIE - XYZ$, YC_bC_r, YIQ and YUV. According to the categorizes of color spaces declared in section 1.1, There are four HVS-based, four application-specific, and four CIE color spaces involved in this study.

For more convenience all channels were considered as subsets of $[0\ldots255]^3$ and all singular point were defined to correspond to zero value in the corresponding channels.

The objects in the sample image (See figure 1)were indexed and their areas were calculated by manual segmentation with repeatedly use of *magic select* tool in *Adobe Photoshop*. To test the performance of spotting in the pre-described standard color spaces, after computing the representation of the sample image in 12 color spaces (37 channels), answers to the following questions were inspected in each of the 37 channels for each of the 8 objects:

1. How much is the most percentile of the object area when it is cut out of the image with the best-selected set of parameters? ($Q_1 \in [0\ldots100]$)
2. When trying to answer the first question, is the background removed completely, without considerable intrusion? ($Q_2 \in \{0,1\}$ mapped to $[0\ldots100]$ in statistics.)

Also a *zero-one* fail rate parameter was defined, showing the situations where the method is unable to distinguish the border of the object. The answers to these questions were acquired and statistically analyzed.

The tests were performed by a subject with 3 years expertise on such segmentation tasks. User was using a *graphic user interfaces*(GUI) developed in *MATLAB 6.5* with scroll bars for tuning parameters (C,T in standard color spaces, a_r, a_g, a_b , C, and T in $PLAC$ and λ in $PCA - PLAC$). He was looking at the original image and the spotted image in two aside windows.

Experimental results are shown in section 4.2 and section 4.3 compares $PLAC$, $PCA - PLAC$, and standard color spaces.

4 Experimental results

4.1 Database

The sample image used in spotting test were taken from 8 objects (*Stapler*, *Infant*, *Red Ball*, *Tin Opener*, *Spring*, *White Ball*, *Blue Ball*, and *Apple*) with different colors put on a smooth surface in the daylight by a digital camera (Figure 1).

4.2 Results

All algorithms were developed in *MATLAB 6.5* with highly optimized code, on an *1100 MHZ Pentium III* personal computer with $256MB$ of RAM.

Answers to the predefined questions were acquired in 37 channels of the 12 color spaces (The

Figure 1: An image taken from eight objects with different colors.

table was too large to be printed in this paper), also in $PLAC$ (Table 1) and $PCA - PLAC$ (Table 2). Tests on the 8 objects were performed 5 times for each object in $PCA - PLAC$ and the average values of all δ_{ij} in different tests on the same object were computed as C along with the average value of all $\tilde{\delta_\lambda}$ as $\bar{\tilde{\delta_\lambda}}$ (Table 2). Table 3 compares fail rate, $\bar{Q_1}$, δ_Q and $\bar{Q_2}$ of the 37 channels, $PLAC$ and $PCA - PLAC$.

Table 1: Spotting results in $PLAC$.

	1	2	3	4
Q_1	86.1	95.2	72.2	56.8
Q_2	100	0	100	100
	5	6	7	8
Q_1	67.8	-	82.5	99.9
Q_2	100	0	100	100

Table 2: Spotting results in $PCA - PLAC$.

	$\bar{Q_1}$	δ_{Q_1}	$\bar{Q_2}$	$\tilde{\delta_\lambda}$	C
1	95	4.73	100	19	96.3
2	94.2	5.67	100	17	93
3	88	5.96	100	66	93
4	66.2	3.86	100	17	94.3
5	91.2	4.16	100	6	96.3
6	48.6	8.56	0	31	71.6
7	74.8	5.26	100	50	93.2
8	99.4	0.80	100	36	98
Average	82.17	4.88	87	30.25	92
Std. Dev.	16.78	2.19	30	19.36	8.94

4.3 Discussion

Investigating the Average and standard deviation of the spotting results in standard channels is insightful. Of course the average value of Q_1 for most channels is higher that 50% but the standard deviation of channels is too high (42.47%) which shows that the method may act poor likely. Of course it must be emphasized that in 73 tests the method was unable to find a reasonable portion of the object or to distinguish the boarder line, which leads to the desperate fail rate of 24.66%.

Over the stimuli the situation is even worse. It is clear that spotting method's success in standard color spaces entirely depends on the object. The best results have been recorded for the *apple*, the *red ball*, the *spring*, the *blue ball* and the *stapler*, which all make distinct loci in the color spaces. The worst result has been captured for the *white ball*, because it is very similar to the background in color scheme.

In the $37 * 8 = 296$ attempts made for cutting the desired object out of the background, only 5 were successful to clear the entire area, which gives the poor mathematical expectation of 1.69%. This event is also very much depending on the subject, as 3 out of the 5 has happened on the 7^{th} object.

In table 1 it is clear that in 6 out of 8 attempts, $PLAC$ was successful to remove the entire background, which gives the hopeful result of 75%. This measure is 87% for $PCA - PLAC$ as shown in table 2.

$PLAC$ has failed to recognize the object in 12.5% of tests, which is half the fail rate of standard methods, having in mind that $PCA-PLAC$ has never failed.

The expectation result of Q_1 in $PLAC$, is 70.06% with standard deviation of 31.68% in contrast with the average of 61.03% and standard deviation of 42.27% in standard color spaces, showing about 10% better results with a smaller standard deviation when comparing $PLAC$ to standard color spaces, making hope that $PLAC$ responds uniformly in the stimuli range. Table 2 shows even better results for $PCA - PLAC$ compared to $PLAC$. The surprising result of 82% expectation value with variance of less than 5% for Q_1 and 87% expectation for Q_2 when λ has changed about 30% shows the robustness of $PCA - PLAC$. It must be emphasized that the average correlation is more than 90%.

It must be emphasized that as the two proposed

$PLAC$s are $1-D$ color spaces, their computation time is at least three times less than ordinary $3-D$ color spaces. Of course compared to the sophisticated *hue-saturation* based color spaces, which use complicated functions, the performance is far better. Also the $PLAC$ and $PCA-PLAC$ are very much appropriate for analog implementation by ordinary circuitry.

The clear disadvantage of $PLAC$ is the tedious tuning job, which reduces its repeatability and needs supervision of human observer, a shortcoming that has been removed in $PCA-PLAC$. It is easy to see that $PCA-PLAC$ needs only one parameter to be tuned by the user in contrast with the two parameters in standard spaces and five parameters in $PLAC$, Also user has no intuition when setting a_r, a_g, a_b, C, T parameters in $PLAC$ in contrast with the meaningful λ parameter in $PCA-PLAC$.

$PCA-PLAC$ has appeared surprising to gain $Q_1 = 46.8\%$ for the peculiar 6^{th} object, where all other methods, even the $PLAC$ have failed.

5 Conclusion

performance of 12 standard color spaces was considered in this study and two measurements along with a fail rate were studied in their respective channels when spotting homogenous regions in a test image containing 8 different colored objects. The measurements concerned the maximum percent of distinguishing power and the background removal ability of each channel for each object. Two color spaces $PLAC$ (parametric) and $PCA-PLAC$ (PCA-based) were proposed and the same tests were performed on them along with the repeatability test on the $PCA-PLAC$. Experimental results showed that rather than the first 6 channels (R,G,B,C,M,Y), the $PLAC$ and $PCA-PLAC$ gained lower fail rates. There were a few channels with the average distinguishing power higher than the $PLAC$ and only one channel better than the $PCA-PLAC$, but the average result of both of them was much higher than the standard color spaces. Also, the standard deviation of the distinguishing power in the $PLAC$ was higher than all others while the results in the $PCA-PLAC$ were even higher than the $PLAC$.

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Table 3: Comparison of results in standard color spaces, $PLAC$ and $PCA-PLAC$.

	Fail	Q_1	δ_{Q_1}	Q_2
R	0	60.02	37.62	0
G	0	73.35	31.94	0
B	0	69.99	34.47	12.5
C	0	66.95	30.28	0
M	0	77.58	30.55	0
Y	0	71.84	33.05	0
K	37.5	42.83	39.18	0
H	37.5	52.27	48.79	12.5
S	12.5	77.81	33.19	0
I	25	55.07	43.12	0
H	37.5	55.29	48.23	12.5
S	25	58.50	48.96	0
V	25	47.45	38.48	0
I_1	25	55.93	46.65	0
I_2	50	46.49	50.44	12.5
I_3	37.5	57.42	47.91	0
L	25	60.94	44.01	0
a^*	37.5	60.97	50.50	0
b^*	37.5	58.90	48.98	0
L	25	60.94	44.01	0
H^o	37.5	61.80	51.19	0
C^*	25	65.54	42.65	0
L	25	60.94	44.01	0
u^*	62.5	34.52	48.06	0
v^*	37.5	57.62	48.45	0
X	25	58.92	44.58	0
Y	25	62.10	44.53	0
Z	12.5	69.97	37.57	0
Y	12.5	64.52	40.08	0
C_b	12.5	74.34	33.50	12.5
C_r	25	68.16	42.92	0
Y	12.5	72.36	40.20	0
I	37.5	48.62	45.83	0
Q	50	43.41	48.78	0
Y	12.5	70.78	41.27	0
U	12.5	84.43	34.41	0
V	50	49.28	52.69	0
Average	24.66	61.03	42.47	1.69
$PCA-PLAC$	0.00	82.18	4.88	87
$PLAC$	12.5	70.06	31.68	75