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Face-priority Auto Focusing with Color Correction

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Abstract: Automatic focusing is very important to high-quality image acquisition for camera system. This paper proposes a new automatic focusing method using skin-color face detection to automatically determine focusing area. In order to overcome the influence of color temperature on the face detection method, we propose a new color correction method by learning a color temperature curve with statistical methods. The color temperature curve is a concise representation of the inverse relation between light sources in the logarithmic color space. The method compensates color shifts of images by locating a set of compensation gains from the trained color temperature regression curve. A comparative setup of experiments is built to verify the effectiveness of the proposed method. Controlled experimental factors include light source, object distance and initial lens position. Modulation transfer function of images is applied to objectively evaluate the image quality before and after the new automatic focusing method. Experimental results show our method has high success rate of face localization, and effectively achieves automatic focusing.

Keywords: Color constancy, color temperature curve, auto-focus, Gaussian mixture models.

INTRODUCTION

Auto-focus [1], auto-white-balance [2,10] and auto-exposure [9] are three critical functions for digital still cameras. Among the three automatic functions, auto-focus (AF) is important in image formation because the quality of the output images depends directly on the performance of the focusing system.

Auto-focus maximizes sharpness of objects in the image to improve image quality. Most of the AF system can be separated into two functional blocks, the analysis block and the control block. The analysis block establishes focusing parameters such as focal length and lens position, and the control block manipulates the lens position to approach the focus range.

The AF system can be categorized to active focusing and passive focusing according to the analysis functional block. Active focusing uses extra devices to measure the distances between objects and lens, and then determines focal length and lens position. Its cost is expensive and is inconvenient to use. Passive focusing needs no extra devices for distance measurement. It determines lens positions by two steps. It measures focus evaluation values (FEVs) within a focusing area of images at a lens position, and then determines the lens position by searching the maximum FEV among a set of lens positions [4]. Since FEV computation is dependent on the focusing area, the success of auto focus greatly relies on the focusing area. That is, FEVs can be meaningful for AF only if objects are located within the focusing area.

Generic settings of focusing area can be divided into fixed focusing area and dynamic focusing area. Fixed focusing area methods, such as three-point line, five-point crossing, nine-point rectangle and fifty-point ellipse, predefine single area or multiple areas to measure FEVs. Fixed focusing methods assume that objects to be focused should be located in the predefined region. Image blurring usually occurs when the assumption fails. Dynamic focusing area methods enable dynamic adjustment of focusing area [5] according to the location of object. Cho *et al.* proposed a manual way to dynamically change the focusing area, which is more flexible than the fixed ways. However, an automatic method to the localization of objects is still the challenge for dynamic focusing area approaches.

Human faces may be a good object for the automatic determination of focusing area. Hence, currently a lot of digital still cameras begin to adopt face detection methods for auto focus. The face detection method is performed before the auto focus and is responsible for the determination of dynamic focusing area. However, only simple face detection methods have been adopted for the implementation in digital still cameras [12,14,15].

Zafeiriou *et al*. [17] and Hjelmas, Low [8] gave excellent reviews of face detection methods and classified them into for four classes. The first class, knowledge-based approach, describes the relationship between facial components such as eyes and mouth to find out face area. The disadvantage is the need of a complex and unstable step for the detection of facial components. Besides, heuristic rules to describe the relationships are applicable only for few situations. Template-matching approach as the second class compares input image with prior matching templates. The disadvantage of this approach is its robustness to scale, illumination, pose and shape change of faces. The third approach performs statistical learning analysis on appearance of faces, which is robust than the template matching method, if huge appearance samples can be successfully collected for the learning. Feature-based approach is the fourth class that aims to find invariant features of a face for detection. It may be the most prevalent face detection method because of its reliability and robustness.

Adaboost face detection [16] and skin-color face detection [3] are two important feature-based methods. Adaboost face detection proposes a rectangle feature for weak classification, and utilizes the Adaboost learning algorithm to select and combine weak classifiers into a strong classifier. Since its rectangle feature belongs to edge feature, misclassification in blur face image is its drawback. Skin-color face detection applied the prior knowledge that the skin tone of human face is an invariant feature. Statistical training of skin color in a color space helps build skin-color model for the detection of face. It can successfully detect blur face. Therefore, most digital still cameras adopt the skin-color method for auto focus [12,14,15]. However, these skin-color models are built based on color histograms or single Gaussian distribution, which are simple models and limit the accuracy of face detection. Besides, since the skin-color face detection method is vulnerable to lighting variations and color deviation, these face-detection auto-focus methods can not be robust under complex environments.

In this paper, a novel skin-color face detection method with color correction is proposed for the auto-focus. The proposed method dynamically determines the focusing area by detecting face location. The face detection method adopts Gaussian Mixture Models (GMMs) to model the probability distribution of skin color, and exploits the Expectation Maximization (EM) algorithm to estimate parameters of the Gaussian Mixture Models. In order to compensate color shifts caused by different light sources, a color temperature correction algorithm is proposed. The algorithm will build the color shift model of different light sources by linear regression of Gaussian models of various light sources. Images compensated by the color temperature correction algorithm will then be used for face detection by a Gaussian mixture skin-color method.

The processing pipeline of this paper is shown in Figure 1. The system and experiments are developed on a digital camera DSP platform to capture Bayer pattern of image data and control camera lens. Raw data from CCD sensor of Bayer pattern comes as input of our system. The image of Bayer pattern has 1:2:1 ratio of red, green, and blue subpixels. An RGB triplet must be computed for each pixel from the Bayer pattern. After this image preprocessing, the color temperature correction algorithm is applied to compensate color shifts of the image. The compensated image is then sent to the auto-focusing process and usual image post-processing such as gamma correction. The auto-focusing has a face detection preprocess to dynamically decide focusing area. The detected face region is passed to the digital signal processor on a DSP-based digital still camera development board to control the lens motor for focusing by searching lens position.

This paper is organized as follows. Section 2 describes the way to build the color temperature curve for various light sources for color temperature correction algorithm. The color-based face detection method is described in Section 3. Section 4 elaborates experimental results which use modulation transfer function as an objectively measurement value to evaluate image quality. Finally Section 5 gives conclusions.

MATERIALS AND METHODS

Colors of human faces may appear different when it is illuminated with different light sources. The color temperature difference of the light sources induces the shift of the reflection spectrum of face from the original skin color in the white light source. When a face is illuminated with a low-temperature light source, the face color becomes reddish due to the distinct color cast from the light source. On the other hand, the high-temperature light source effects bluish in face color. Especially, a face illuminated with incandescent light source will be yellowish, which causes background colors close to the skin color and affects the skin-color-based detection for face.

Auto-white-balance and color constancy have been an important research topic to compensate color shift due to light sources. The most widely used approach is based on the gray-world assumption [10]. The assumption of the approach is that average color in a scene is neutral or gray. The average color of the scene can then be calculated to zero-out any color bias. For scenes with strong and dominant color objects, the assumption does not hold and the compensation will fail. Another commonly used approach is the white-patch assumption that assumes the red, green, and blue values of the brightest point in the image should be the same. The approach can not work when the scene contains a relatively large background or a large object having the same color. Gamut mapping [2] and color by correlation [6] are proposed to give weaker assumptions on the scene. These methods compare correlation of color gamuts between the captured image and a number of reference illuminants. The most likely illuminant is identified by the correlation. The correlation approach has better performance only if abundant training images are available for different combination of illumination environments.

This paper proposes a novel color temperature curve method for color compensation. The method employs the theory derived in [7] that inverse linear relation of light sources sustains in the log (G/R) - log (G/B) space. A mathematical proof is given for the seven surface colors (green, yellow, white, blue, purple, orange and red) under ten Planckian illuminants of color temperatures from 2800K to 10,000K. However, no empirical methods are developed in literatures. In this paper, a linear Gaussian regression method is devised to estimate the linear relation of color temperatures of light sources. The estimated color temperature curve will be used for illuminant determination and color correction. This method has no gray-world and white-patch assumptions, and gives better performance in both learning and correction speed than that of the correlation approaches, because of less training samples and reference illuminants.

Color Temperature Curve Estimation

The linear property of color temperature curve has to be established by a set of few learning samples. Fig. 2 shows the process to learn the color temperature curve. Notice that we did not use an RGB image captured from a camera, because the output image of a camera system has been adjusted by the default auto-white-balance (AWB) method. Therefore, we have to configure the camera system to stop the AWB function in order to obtain raw images of Bayer pattern arrangement. We then convert the raw images into RGB image, and transform the pixel values into the log space. To obtain the linear property in the log space, Gaussian modeling of each light source is built. Linear regression method is then applied to find the color temperature curve.

The training data is obtained using a DSP-based CCD camera system with resolution of 2864x2160 pixels and 12-bit pixel depth. The training image is captured from a standard plate for color research, the GretagMacbeth ColorChecker Chart. GretagMacbeth SpectraLight III are used for illuminating the chart with 4 standard referenced light sources, incandescent, cool white, daylight, and horizon. Each light source illuminates the chart at a color temperature. We add three more color temperatures of 2700K, 4000K and 6400K by one light source, the WALSIN lamp. Captured pixels within the gray areas under the ColorChecker Chart are used for training. Only the four gray areas from gray areas 2 to 5 are adopted due to that the minimum-gray area is noisy and the maximum-gray area is saturated.

Fig. 3 shows the log(G/R)-log(G/B) space of the pixels in the four gray areas. It can be seen that there is an inverse linear relation between the seven clouds. The observation fits the mathematical foundation in [7]. However, the pixel values in the gray area 2 are noisy because we can see that the clouds have large deviations. The overlapping between clouds in the gray area 2 is too much. The deviation is small and the overlapping is not serious for the gray area 5.

We use a statistical analysis method to show that the log-space plot of gray area 4 will be a good choice to learn the color temperature curve. The two-dimensional Gaussian function is applied to model the clouds of the seven illuminants from gray areas 2 to 5. Means of the Gaussian functions in a gray area are fitted by linear regression. A coefficient of determination R^2 represents the fitting measure of the regression line. Three factors, variance, overlapping percentage and the R^2, are inversely normalized to the interval [0, 1] and averaged to give a goodness index of the gray area being chosen for the color temperature curve.

In Table 1 the gray area 4 has the maximum goodness index. The color temperature curve is shown in Fig. 4. Any point in the color temperature curve represents a color shift produced by a kind of light source with a specific color temperature. Therefore, for a point $x=(x_{logG/R}, x_{logG/B})$ located in the curve, $\exp(x_{logG/R})$ and $\exp(x_{logG/B})$ are the color shifts of the point represented as ratios of G/R and G/B. The two values are called compensation gains and can be used for color correction.

Color Adjustment

A new captured image will be adjusted in order to correct the dominant color cast caused by light sources. The dominant color cast has to be estimated first. The trained color temperature curve is utilized to find compensation gains to correct the red, green, and blue components of the new image.

The algorithm samples the new image to extract a few pixels for the estimation of dominant color cast. Average values of red, green, and blue components are calculated from these sampled pixels. The averaged pixel value is converted to a point X in the log(G/R)-log(G/B) space, where the X point represents the estimated dominant color cast of the new image.

Since the color cast point may not fall into the color temperature curve, a geometric projection of the *X* point into the curve is calculated. The projected point *X'* of *X* locates on the color temperature curve with the coordinates ($X'_{logG/R}$, $X'_{logG/B}$), which can be used as the compensation gains to correct the image.

Fig. 5 illustrates the correction of color temperature using the GretagMacbeth ColorChecker chart. The algorithm can compensate the color temperature deviation to overcome the influence of outside light.

The Skin-Color Face Detection

Skin color method for face detection is robust to geometry, scale, pose, expression, occlusion, and sharp variations. Most importantly, the method can resist to the blur of face image. In this paper, the probability model of skin color is built on the chromatic space of the YCbCr color space in order to reduce the influence of environmental luminance.

GMM is adopted for the modeling of the probability distribution of skin colors. Assume *x* is the chromatic components of a skin color, the formula of combining multiple Gaussian functions is described as below:

$$p(x) = \sum_{i=1}^{M} \frac{\pi_i}{(2\pi)^{n/2} \left|\Sigma_i\right|^{1/2}} exp\left[-\frac{1}{2}(x-\mu_i)^T \Sigma_i^{-1}(x-\mu_i)\right], \quad (1)$$

where *M* is the number of Gaussians, π_i is weight value of the *i*th Gaussian, *n* is the dimension of the chromatic space, and μ_i and Σ_i are the mean and covariance matrix of the *i*th Gaussian.

EM algorithm [13] is adopted to estimate the parameters π_i, μ_i, Σ_i of the GMM. The algorithm has two steps: an expectation step to evaluate the posterior probabilities for each mixture component, and a maximization step for the update of the mixture components. The E and M steps will iterate until convergence. The EM algorithm for the GMM is formulated as follows:

1. Expectation (E step) ：

$$E(z_{ij}) = \frac{\pi_i^t p(x_j \mid \mu_i^t, \Sigma_i^t)}{\sum_{p=1}^{M} \pi_p p(x_j \mid \mu_p^t, \Sigma_p^t)}, \quad (2)$$

   where $E(z_{ij})$ is the probability of data *j* belonging to the Gaussian model *i* in terms of possession degree, and *t* is the iteration index.

2. Maximization (M step) ：The results of E step will be used to update the GMM parameters.

$$\pi_i^{t+1} = \frac{1}{N}\sum_{j=1}^{N} E(z_{ij}), \quad (3)$$

$$\mu_i^{t+1} = \frac{1}{N\pi_i^{t+1}}\sum_{j=1}^{N} E(z_{ij})x_j, \quad (4)$$

$$\Sigma_i^{t+1} = \frac{1}{N\pi_i^{t+1}}\sum_{j=1}^{N} E(z_{ij})\{(x_j-\mu_i^{t+1})(x_j-\mu_i^{t+1})^T\}, \quad (5)$$

   where *N* is the number of training pixels of skin color.

3. Stopping criteria for the decision of convergence.

$$\sum_{i=1}^{M} \left\|\theta_i^{t+1} - \theta_i^t\right\| < Threshold \quad , \quad (6)$$

   where θ is the parameter vector of (π, μ, Σ).

The above GMM and EM algorithm can decide whether a pixel belongs to skin color, which produces a binary image. Mathematical morphology is then applied to the binarized image by erosion and opening operators to eliminate noise, and dilation and closing operators to eliminate small holes and fill small gaps. Connected component labeling is used to obtain a labeled image. A union-find algorithm with 4-neighborhood is applied to check uniform-intensity pixels and connect uniform labels in the binary image.

RESULTS AND DISCUSSION

In the experiments images are captured from a digital still camera development platform, which is Coach 8M with a 32-bit MIPS DSP chip. The experimental flow is shown in Fig. 6. In training stage images are captured from the development platform with disabled AF and AWB functions. The parameters of color temperature curve and GMM of skin colors are performed in a computer. In test stage, images are still captured from the development platform. After color correction and face detection in the computer, the focusing area is sent back to the development platform to control the lens and find the lens position. The FEVs in the development platform adopts Sobel edge detection to extract highfrequency components. The lens position is determined by the search by percentage drop method [4] which can quickly find the lens position without searching the full range of positions.

Three experimental control factors, light source, object distance and initial lens position, are designed in our experiments. Experimental results will show the influence of the three control factors to the effectiveness of the algorithm. The experimental environment with the three control factors is illustrated in Fig. 7. The distance between the object and the camera can be 3M, 2.5M, 2M, and 1.5M. The object distance can affect the size of the object image and focal length of the camera, which may have an effect on the proposed method. The light source on the right side of the camera can have color temperatures of 2700K, 4000K and 6400K. Since the development platform use the search by percentage drop method to find the lens position, initial lens position is important for auto-focusing even the focusing area has been determined by our method. Four initial positions, 4.6mm, 5.1mm, 5.6mm and 6.2mm, are decided to be changed in our experiments. There are 48 controlled conditions in our environment.

The charts 1 and 2 in the Fig. 7 have the same pattern that are used to measure image quality. The chart 1 is always placed in front of the camera with a fixed distance of 0.4M. The chart 2 is placed on the side of the object, which means the distance between the camera and the chart 2 is always changed during the experiment. Since the chart 2 has the same camera distance with the object, the experiment obtains high-quality object image when the chart 2 has high image quality. We verify the image quality of the chart 2 using the Modulation Transfer Function (MTF) [11]. The MTF is a way to quantify image quality by measuring the contrast of the image. The contrast of the image is defined by a set of sine-wave change patterns with different frequencies. The stripes in the charts have different compactness levels from the left to the right to measure the increased contrast level.

To objectively evaluate the performance of our method, the MTF values of charts 1 and 2 are employed. Fig. 8 exhibits the change of the MTF values before and after the proposed auto-focusing method. It demonstrates that the MTF values of the chart 2 become larger after the auto-focusing, and the MTF values of the chart 1 become smaller after the auto-focusing.

A more complete experiment is established to evaluate the performance of the MTF value change. There are three persons captured as objects in our experimental environment. Each person is taken two pictures for each of the 48 controlled conditions before the auto-focusing. That is, each object has 96 experimental images. The 288 test images and the 288 results images of the test images are measured by the MTF. Eq. (7) is the evaluation function to quantify the performance.

$$f(x_1, x_2, x_3, x_4) = 0.5 \times \frac{x_1 - x_3}{M_1} + 0.5 \times \frac{x_4 - x_2}{M_2}, \tag{7}$$

where x_1 and x_2 are the MTF values of the charts 1 and 2 before the auto-focusing, x_3 and x_4 are the MTF values of the charts 1 and 2 after the auto-focusing, $M_1 = max\ \{\ x^i_1 - x^i_3 \mid 1 \le i \le 288\ \}$, and $M_2 = max\ \{\ x^i_4 - x^i_2 \mid 1 \le i \le 288\ \}$. Table 2 shows the mean MTF values of each controlling factors by averaging out the 288 test images and result images. The results in the success rate column are obtained by a decision formula: $f(x_1, x_2, x_3, x_4) > T$, where T is a success threshold that equals to 0.4.

The success rates for each controlled factors are highly satisfactory. The total success rate by averaging all test images is 97.2%. We also manually evaluate the success rate by an independent person and obtain a 97.6% success rate, which means that the objectively evaluated performance can match subjectively evaluated performance of image quality.

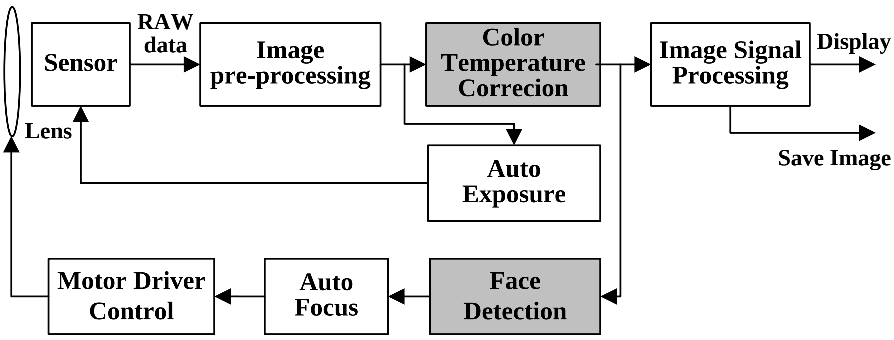

Fig-1: The proposed pipeline for auto-focusing of digital still camera. The automatic white balance is replaced with a new approach called color temperature correction. The new process, face detection, is preceded to the ordinary auto-focus process

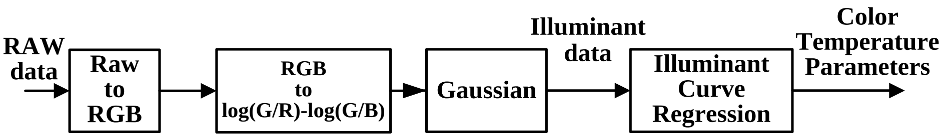

Fig-2: The training process of the color temperature curve

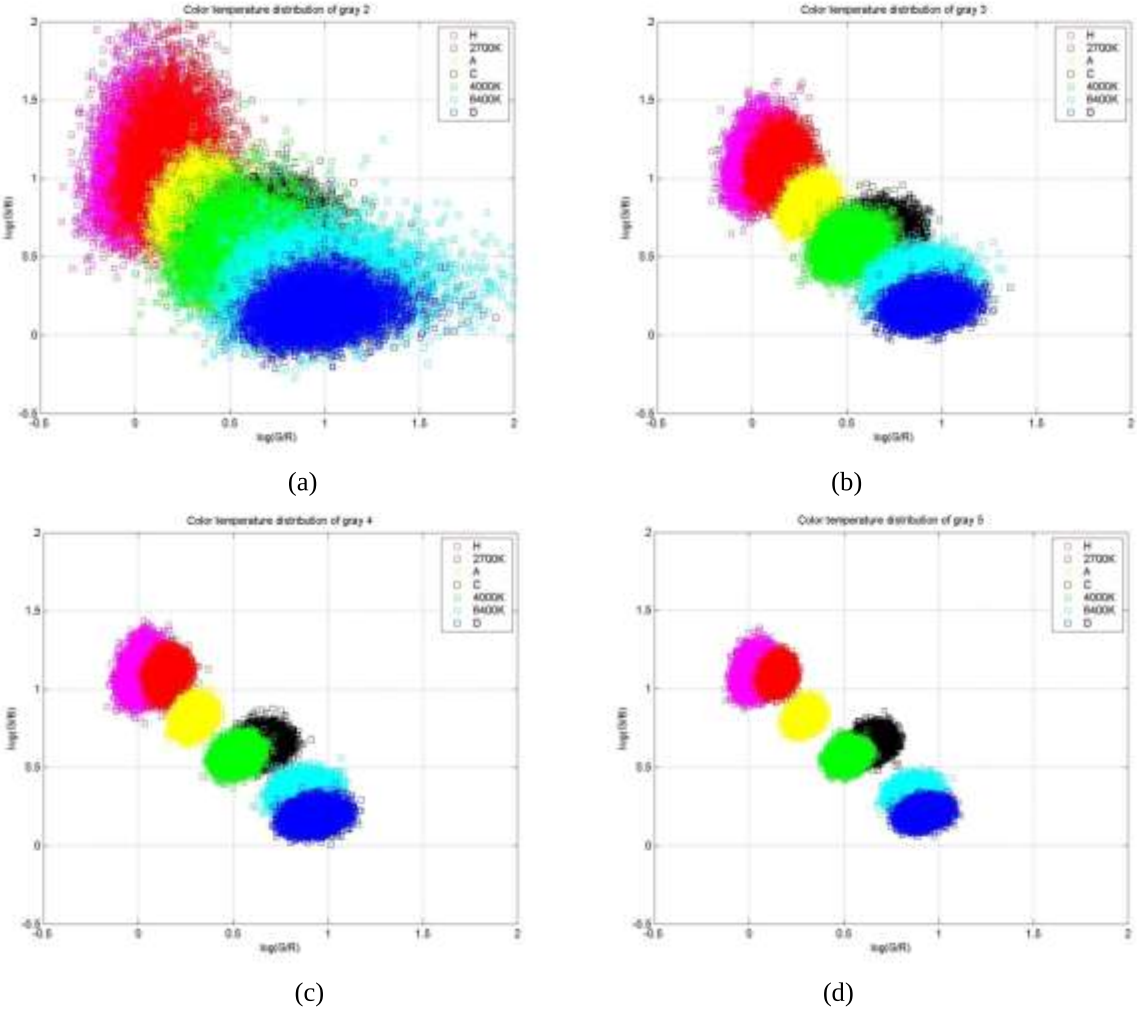

Fig-3: Gray distribution under the 7 illuminants. They are pink dots for horizon light, red dots for 2700K light, yellow dots for incandescent light, black dots for cool white, green dots for 4000K light, cyan dots for 6400K light, and blue dots for daylight. (a) Gray 2, (b) gray 3, (c) gray 4, (d) gray 5

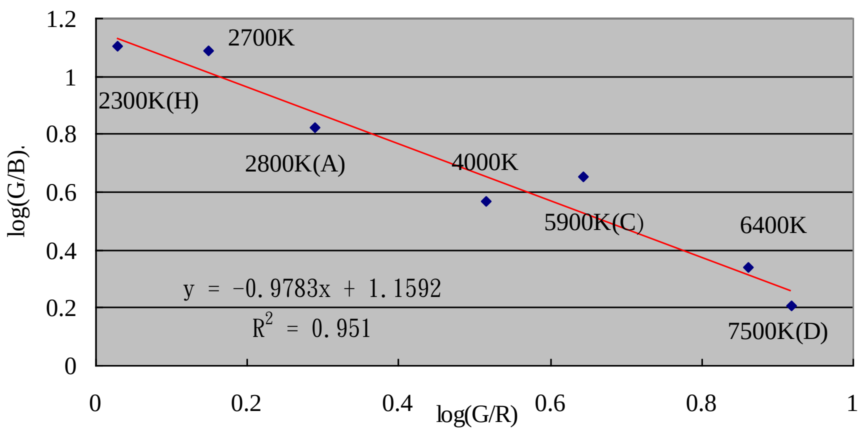

Fig-4: Color temperature curve obtained from the gray area 4

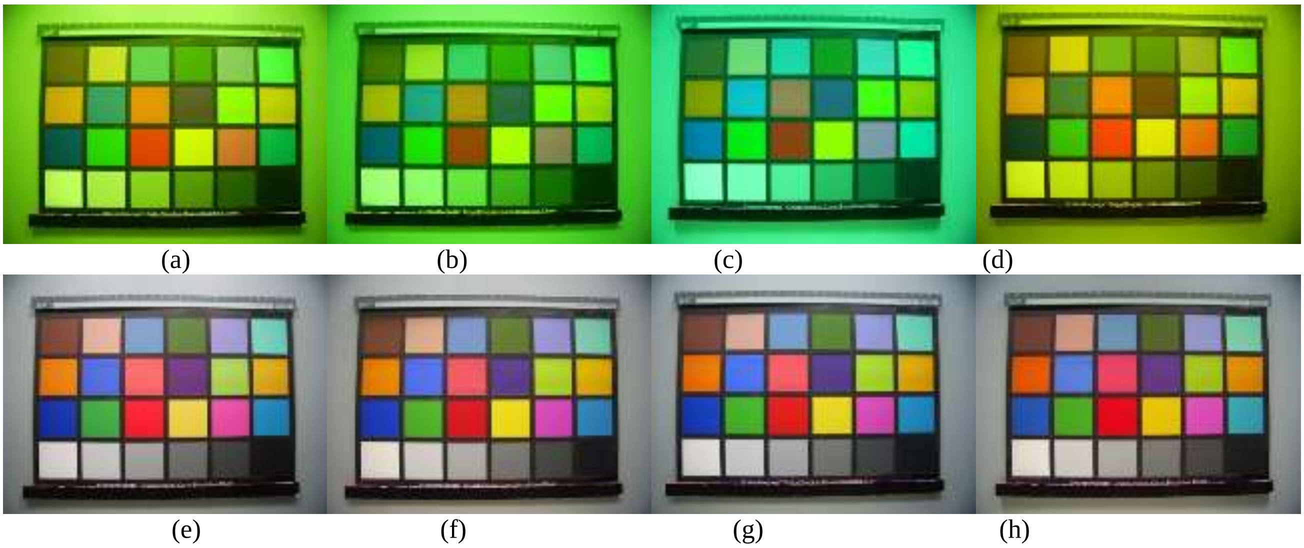

Fig-5: The results of color temperature correction. (a)~(d) Original images under incandescent, cool white, daylight, and horizon light sources. (e)~(h) Corrected images of (a)~(d)

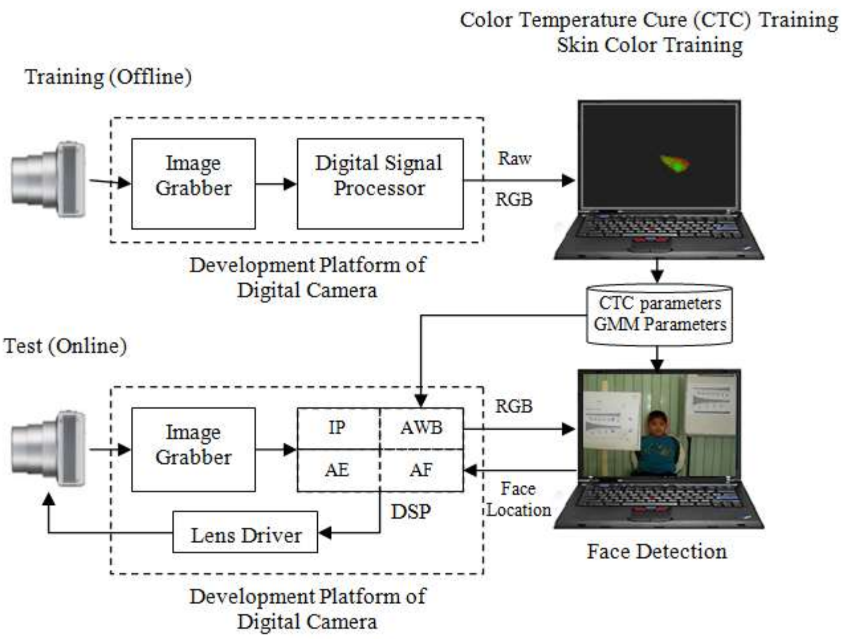

Fig-6: Process flow of the experiments

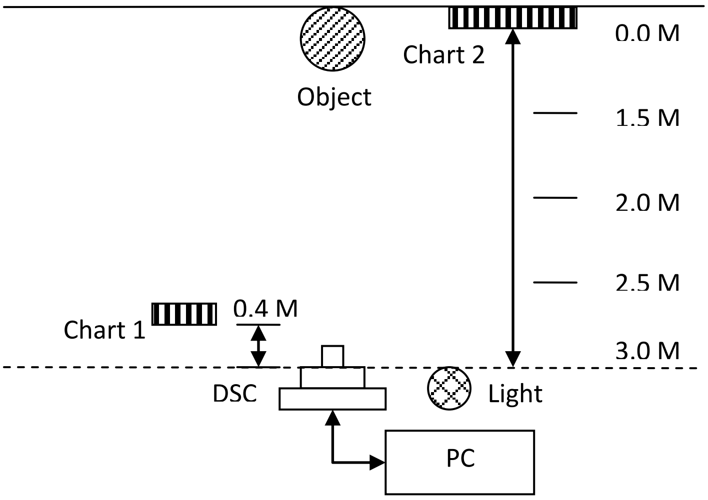

Fig-7: The experimental environment. Charts 1 and 2 are the same pattern to help evaluate the MTF values

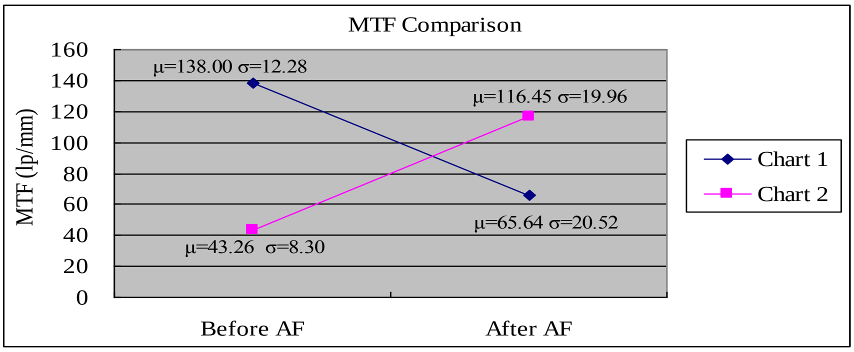

Fig- 8: Result comparison of MTF

Table-1: The goodness index of the four gray areas computed by variance, overlap percentage and coefficient of determination R^2

Gray area	σ_x^2	σ_y^2	Overlap %	$1-R^2$	Goodness index
2	0.02630	0.0306	46.65%	0.054	0
3	0.00629	0.0076	21.43%	0.047	0.763
4	0.00298	0.0035	12.76%	0.044	0.970
5	0.00187	0.0022	11.69%	0.049	0.875

Table-2: The MTF values for each controlled factors.

Factors	Performance	x_1	x_2	x_3	x_4	$f(x_1, x_2, x_3, x_4)$	Success rate
Light Source	2700K	139.51	42.92	62.92	121.52	0.72	99.0%
	4000K	141.59	40.22	63.61	111.78	0.70	96.9%
	6400K	132.60	46.82	67.96	118.22	0.63	97.9%
Object Distance	1.5M	139.57	46.99	70.50	116.28	0.64	98.6%
	2.0M	141.44	43.03	67.02	112.73	0.67	97.2%
	2.5M	141.40	43.15	61.50	120.61	0.73	97.2%
	3.0M	129.60	43.15	63.54	117.64	0.67	95.8%
Focal Length	4.6mm	147.20	46.63	75.94	127.83	0.71	97.2%
	5.1mm	141.44	45.67	69.50	117.92	0.67	95.8%
	5.6mm	134.16	41.55	60.90	113.61	0.68	97.2%
	6.2mm	128.16	38.67	53.30	110.77	0.68	98.6%

CONCLUSION

In this paper, we propose a novel auto-focusing method by dynamically determine face location to be the focusing area. The method proposes a new color correction method by color temperature curve. The inverse linear relation of light sources is learned by employing linear regression of grayed pixel values. Gaussian probability modeling and a goodness index are devised to build the color temperature curve. Color adjusted images are then sent for face detection process. The face detection process applies Gaussian mixture model and the expectation maximization algorithm to establish the probability model of skin colors. A complete experiment is setup based on a digital still camera development platform and an environment of 48 controlled factors. The experimental results achieving 97.2% success rate demonstrate that the proposed method can detect face area under different environmental light sources, and automatically localize the face position to achieve focusing function of face detection. The proposed method can not only be applied to auto-focusing, but also to other function units of digital still camera. Future work could apply the method on auto-exposure unit to dynamically determine the exposure window and adjust the exposure weight to correct luminance of images.

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