An Illumination Compensation Method for Images under Variable Lighting Condition

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***Abstract*—this paper presents an illumination compensation method for images under variable lighting condition. The algorithm consists of two processes. First, the camera response function is identified as a nonlinear model of the camera under dynamic illumination. Then an image with a wider dynamic range is obtained online by fusing several images taken under different exposures of the same scene. The algorithm is applied to the four-legged robot soccer competition and is verified to be superior to some traditional schemes.**

***Keyword:* variable lighting, illumination compensation, robot soccer**

I. INTRODUCTION

The Robocup four-legged league [1] [2] is an annual robot soccer competition, which currently uses Sony Aibo ERS-7 robots as its standard platform. To date, the games all play on a small field under constant, bright lighting condition. However, the future Robocup could possibility require to play under a changing and finally natural lighting condition [3], which means that it is very important whether the vision module can run stably under varied illumination for serving other processing modules, such as to achieve reliable localization.

There are several challenges faced by a robot vision system under a varied lighting condition. First, the dynamic range of the nature light can reach 100 000 000: 1 [4]. It is beyond the perceivable range of an ordinary imaging sensor so that some details in the dark or bright areas may not be detected. Second, nearly all teams took colors as the main visual features, which are highly sensitive to the changes in light [5] [6]. Further more, most vision algorithms assumed that brightness measured by the imaging system is linearly related to scene radiance. In practice, the relation between scene radiance and measured brightness is generally nonlinear, since there are a number of nonlinear mappings involved in the process of image acquisition (see Fig. 1).

This paper presents a compensating method to deal with the issues associated with variable illumination. The remainder of this paper is organized as follows. The method consists of two processes. First, the camera response function is identified offline as a nonlinear model of the camera under dynamic illumination [7]. Then an image with wider dynamic range is obtained online by combining several images taken under different exposures of the same scene. It is experimentally verified to be an effective image pre-processing method to obtain an enhanced and uniform image under variable lighting condition. In section 2, technical details of the algorithm are given; section 3 provides the experimental results and conducts a comparison with other image enhancement schemes; conclusions are given in section 4.

II. THE ILLUMINATION COMPENSATION ALGORITHM

The overall structure of the presented algorithm is shown in Fig. 2. In the offline part, the camera response function is obtained by taking several pictures under different exposures of a scene, which is presented in a table and can be used to transfer measured brightness to image irradiance. In the online part, the robot takes two different exposed pictures at one time, then transfers the brightness of these two pictures to two radiance maps, finally it combines and compresses the two radiance maps into one desired picture.

A. Identification of the camera response function

In a common imaging system, the relationship between image irradiance E and scene radiance L can be expressed as [8]:

$$E = L \times \frac{\pi}{4} \times (\frac{d}{h})^2 \times \cos^4 \phi \qquad (1)$$

where, h is the focal length of the camera lens, d is the diameter of its aperture and ϕ is the pixel's angle from the optical axis. If the imaging system is ideal, the captured brightness would be $B = E \times t$, where t refers to the exposure time. This ideal imaging system's response function can then be written as:

$$B = L \times k \times e, \qquad (2)$$

where, $k = \frac{\cos^4 \phi}{h^2}$ and $e = \frac{\pi}{4} \times d^2 \times t$ represents the image's exposure. Suppose the actual camera response function can be approximated by

$$I = f(B) = \sum_{n=0}^{N} c_n B^n \qquad (3)$$

where B is the brightness measured by the imaging system and I is the image irradiance. Since the pictures captured by Sony Aibo are stored in the YUV color space, B is assumed to be the value of Y in this paper. Assume two pictures of a same scene

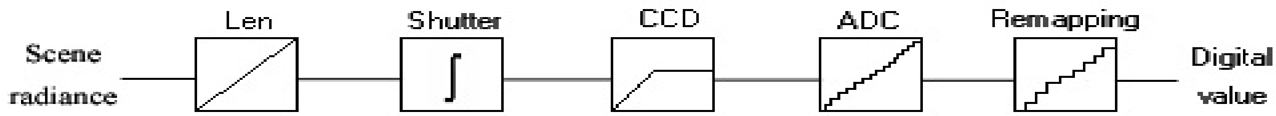

Figure 1 Image Acquisition Pipeline

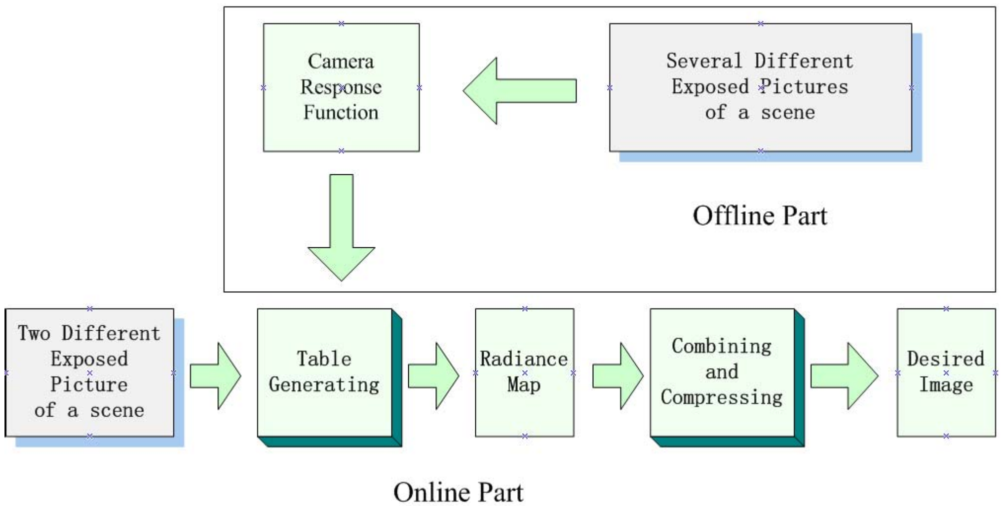

Figure 2 Structure of the image pre-processing algorithm

taken under different exposures, e_q and e_{q+1} ($e_q < e_{q+1}$). The irradiance ratio $R_{q,q+1}$ between these two pictures at any given pixel p can be written using (2)

$$\frac{I_{p,q}}{I_{p,q+1}} = \frac{L_p \times k_p \times e_q}{L_p \times k_p \times e_{q+1}} = R_{q,q+1} . \tag{4}$$

Substituting (3) into (4) yields:

$$\frac{f(B_{p,q})}{f(B_{p,q+1})} = \frac{\sum_{n=0}^{N} c_n B_{p,q}^n}{\sum_{n=0}^{N} c_n B_{p,q+1}^n} = R_{q,q+1} . \tag{5}$$

Taking summation of Y values of the two pictures, Y_q and Y_{q+1}, we can estimate that

$$R_{q,q+1} = \frac{Y_q}{Y_{q+1}} . \tag{6}$$

Then, the response function can be recovered by optimizing an error square derived from (5):

$$\in = \sum_{q=1}^{Q-1} \sum_{p=1}^{P} [\sum_{n=0}^{N} c_n M_{p,q}^n - R_{q,q+1} \times \sum_{n=0}^{N} c_n M_{p,q+1}^n]^2 , \tag{7}$$

where Q is the total number of images used for identification, P is the total number of pixels in the image. If we normalize B such that $0 \le B \le 1$ and add a constraint that $f(1) = I_{\max}$, we will get:

$$C_n = I_{\max} - \sum_{n=0}^{N-1} c_n . \tag{8}$$

The response function coefficients can thus be estimated by optimization of (7):

$$\frac{\partial \in}{\partial c_n} = 0 . \tag{9}$$

The solution of (7) works in a recursive way that, for an unknown $R_{q,q+1}$, we use the current ratio estimate $R_{q,q+1}^{(k-1)}$ to compute the optimal coefficients $c_n^{(k)}$. Then, the ratio estimate can be updated by using (5):

$$R_{q,q+1}^{(k)} = \frac{\sum_{p=1}^{P} \sum_{n=0}^{N} c_n B_{p,q}^n}{\sum_{p=1}^{P} \sum_{n=0}^{N} c_n B_{p,q+1}^n} . \tag{10}$$

The initial ratio estimate $R_{q,q+1}^{(0)}$ of this recursive optimization is computed by using (6). The above recursive process repeats until:

$$| f^{(k)}(B) - f^{(k-1)}(B) | < \sigma, \forall B , \tag{11}$$

where σ is a small number.

However, the error square optimization may exhibit unacceptable deviation due to image quantization errors or the unfit approximation. So we introduce a method to check the accuracy of the solution. Assume the equivalent linear system can be written in:

$$Ax = B \; . \tag{12}$$

Suppose the solution is *x'*. A measure of the solution accuracy can be defined as

$$p = \frac{norm(Ax')}{norm(B)} \; . \tag{13}$$

By checking this measure, a solution can be accepted if $p \in [1-\theta, 1+\theta]$.The upper bounder of order *N* could be set in order to run the algorithm repeatedly to find out the optimal *N* which provides the lowest error bound σ . In our experiments, we used three pictures of a scene with different exposures and with $N = 5$ and $\theta = 0.2$. After obtaining the camera response function, a table can be generated for simplifying the online calculation.

B. Irradiance estimation by fusion of images with different exposures

The obtained camera response function provides mapping between image brightness and irradiance. In the online part, two or more images can be taken under different exposures and then they are fused into one image under certain irradiance. The fused image is expected to have richer information from different exposures and be less relevant to varied illumination. Suppose two images B_1 and B_2 have been captured with two different exposures. The brightness B_1 and B_2 can be transferred to image irradiance I_1 and I_2 by using the generated camera response function table.

$$\begin{aligned} I_1 &= f(B_1) \\ I_2 &= f(B_2) \end{aligned} \; . \tag{14}$$

The actual irradiance under the first exposure can be better recovered by fusing irradiance I_1 and I_2.

$$I' = \frac{w(B_2) \times I_2 \times R_{1,2} + w(B_1) \times I_1}{w(B_2) + w(B_1)} \, , \tag{15}$$

where $R_{1,\,2}$ can be determined by (10), and $w(B)$ is a weight function. The pixels whose derivative is near one should play a more important role in the process of fusion because brightness *B*'s around $f'(B) = 1, B \in [0,1]$ are able to respond more adequately to irradiance and can thus provide more authentic information about *I*. So the weighting function is chosen below:

$$w(B) = \begin{cases} 1/\,|\mathrm{B} - \mu{*}255\,| & \mathrm{B} \neq \mu \\ 1 & \mathrm{B} = \mu \end{cases} \; B \in [0,255] \, , \tag{16}$$

where μ is the solution of $f'(\mu) = 1$. The obtained irradiance *I'* will be influenced less by changing illumination. In order to convert *I'* back to an image, we need to rescale its values into an 8-bits format used by the vision system. Assuming the maximum value of image irradiance is $I_{\max}$, we apply the following scaling function to the fused irradiance:

$$I = (I' / I_{\max}) \times 255 \, , \tag{17}$$

and a rectified image to represent actual irradiance can be obtained.

III. Experiment Results

In the experiments, we used several different scenes to identify the associated camera response functions using the algorithm presented in section Ⅱ. Fig. 3 draws the curves of four results and Table Ⅰ lists the corresponding coefficients. It can be observed that the curve *H* deviates from the others. This can be examined by measure *p* in (13), indicating a higher identification error due to image quantification error. In fact, the problem can be alleviated by utilizing more pictures in the process of identification. From experiments, three pictures with an exposure ratio $R_{q,q+1} = 0.5$ could achieve a satisfied effect. The differences between the curves in Fig. 3 can be examined by

$$g(f_1(x), f_2(x)) = \int_0^1 (f_1(x) - f_2(x))^2 \, dx \, , \tag{18}$$

which reflects the area between $f_1(x)$ and $f_2(x)$. From Table Ⅱ, we can find that the areas between curve *y1*, *y2* and *y3* are quite small, which means the identification results are very close. Therefore the consistency of the identification in terms of different scenes indicates that the camera response function is fairly robust and stable in various environments.

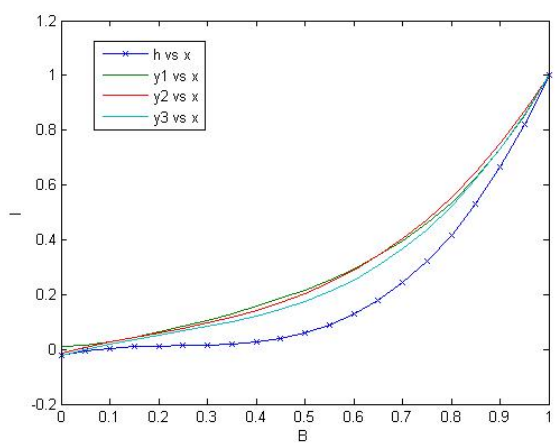

Figure 3 Camera Response Function

For the strict time constraint required by real time applications, we take just two pictures of a scene in the online part. The result of applying the algorithm Ⅱ can be shown in Fig. 4 (for the convenience of comparison study, only the *Y* channel of the picture is presented.). It is obvious that the proposed algorithm is able to perceive the details in both dark and bright areas and exhibits a high dynamic range; further more, the brightness of the resulted image Fig. 4 (c) is indeed proportional to the scene radiance.

For the purpose of evaluation of the proposed algorithm, the same pictures were supplied to the conventional methods for preprocessing, e.g. Histogram Equalization and Retinex. Experimental results are illustrated in Fig. 5 and Fig. 6. Histogram equalization and Retinex can extend the contrast in the low gray level while compress high gray level, but both of them tends to introduce noise or lose details at the dark end or bright end. The proposed illumination compensation method makes use of both dark and bright pictures and results in a linear brightness relation with the actual irradiance. In addition, we can find our method is stable from Table Ⅲ.

IV. CONCLUSIONS

This paper has proposed a novel image pre-processing method to cope with degeneration on image quality due to changing illumination. The proposed method attempted to recover the actual irradiance using several images taken with different exposures. It is able to compensate illumination variation and expand perceivable dynamic range so that a clearer image can be obtained. In comparison with other conventional image enhancement techniques, the proposed method can exhibit a more stable and uniform performance across a wider dynamic range, which was verified by comparative experiments. The preprocessing algorithm has been successfully implemented in our four-legged robot soccer team for achieving reliable and accurate localization under variable illumination. While the method has been tailored for soccer-playing robots, it can be applied to other situations which need image processing or recognition in an environment with changeable illumination.

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TABLE I. COEFFICIENT OF THE CAMERA RESPONSE FUNCTION

	C_0	C_1	C_2	C_3	C_4
y1	0.008734	0.105655	1.104999	-1.712859	1.493472
y2	-0.014536	0.453979	-0.632037	1.192594	0
y3	-0.023847	0.519230	-0.999286	1.503902	0
H	-0.020461	0.380063	-1.516181	2.156579	0

TABLE II. SIMILARITY BETWEEN CURVES

	$g(f_{Y1}(x), f_{Y2}(x))$	$g(f_{Y1}(x), f_{Y3}(x))$	$g(f_{Y2}(x), f_{Y3}(x))$	$g(f_{Y1}(x), f_H(x))$
$g(f_1(x), f_2(x))$	1.4606e-004	7.6163e-004	6.0135e-004	0.0123

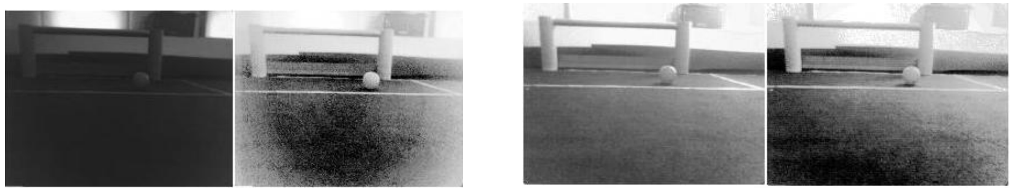
TABLE III. COMPARISON OF THREE METHODS UNDER FOUR DIFFERENT LIGHTING CONDITIONS

	Average *Y* in Lighting Condition Ⅰ	**Average *Y* in Lighting Condition Ⅱ**	**Average *Y* in Lighting Condition Ⅲ**	**Average *Y* in Lighting Condition Ⅳ**	**Variance**
Our method	114.96	109.14	90	96.7	129.6904
Histogram equalization	134.2023	132.2625	133.6767	130.438	2.835581
Retinex	219.2	157.4	130.7	97.37	2660.118

We take pictures of a same scene under four different lighting conditions. The average *Y* values of three methods' results are listed in the table. Our method and Histogram equalization method's variance are small. But the Histogram equalization method tends to introduce noisy which can be seen in Fig. 5

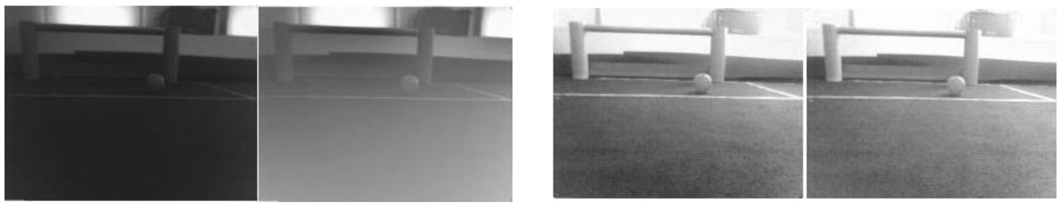
(a) (b) (c)

Figure 4 (a) is a picture with low exposure and (b) is a picture with high exposure. It is obviously that (a) loses the details in dark area of the scene while (b) loses the details in bright area of the scene. (c) is the fused result of the algorithm with clear image details about the scene.



(a) (b)

Figure 5 Histogram equalization. (a) shows the result using the picture with low exposure while (b) shows the result using the picture with high exposure. Obviously, the Histogram equalization method introduce noisy to the result.



(a) (b)

Figure 6 Retinex (a) Retinex enhancement to the picture with low exposure; (b) Retinex enhancement to the picture with high exposure

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