

A Multi-Layer Model for Adaptive Pre-processing of Panoramic Images

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Abstract—Panoramic image pre-processing is one of key technologies in subsequent image processing and applications. An adaptive pre-processing multi-layer model for the sequences of panoramic images formed by six cameras is proposed in this paper. The algorithm develops a luminance classification criterion for different level of panoramic image based on the distribution of the statistical characteristics and threshold judgment. The criterion is able to cope with the image pre-processing effectively and stably when luminance altered. By this method, each pixel is adaptive based on illumination levels, resulting in the development of visual effect. Experiment results show that the proposed algorithm can significantly improve the quality of 3D panoramic images in complex environments.

Index Terms—Panoramic Image, Self-adaptation, Pre-processing

I. INTRODUCTION

The so-called panoramic image with large-size and high-resolution consists of two or more ordinary images that are taken from different angles with character of the same overlapping areas [1, 2, 3]. With its special advantage of “seeing more”, panoramic images have wide applications in geographic information, 3D TV, displaying for products, public safety, battlefield reconnaissance, environmental monitoring and other fields [4]. Apparently, wide and effective application in society validates the research necessity of panoramic images. Some problems have been unfolding in the process of its further researching. The photos used to form the panoramic image are always acquired by specially adapted vehicle with six or more directional cameras, leading to differences in luminance and chrominance. Therefore, the spliced panoramic image may have uneven illumination and non-uniformity chrominance. What’s worse, the panoramic images are achieved with time & location dependent, so these images also have differences in terms of illumination.

Accordingly, adaptive pre-processing technologies should be applied into panoramic images before post-processing and showing application, which has become a research focus and cutting-edge in the field of computer vision and intelligent visual surveillance [5, 6].

360-degree view panoramic images of the whole city always produce a huge amount of data, e.g., hundreds of TB. Adaptive pre-processing algorithms based on luminance feature of panoramic images are demonstrated well to improve the efficiency of image processing compared to mutual handing which is inefficient and ineffective, and thus it has been widely used in the applications such as digital city and street view. The key of brightness-based method is to solve the problem of uneven illumination and chrominance in images caused by directional cameras and diverse environments. Several factors such as illumination change, motion blurring and saturation altered should be considered simultaneously while designing an adaptive pre-processing algorithm. And thus the fully adaptive processing models are difficult to establish due to the complexity of environments. Therefore, the current study is to establish corresponding model for the actual needs of a particular scene. It promotes scholars carrying out a large number of researches to upgrade panoramic images quality automatically and efficiently.

Histogram equalization [7, 8] is widely used in image enhancement. Being mapped to a uniform distribution, histogram will easily bring three problems: the wrong contour, introducing noise and appearance distortion. The Gray-level Grouping method used by Chen [9] which helps reducing the histogram beam and generating a quasi-uniform distribution of the histogram enhances the image contrast. The transform-based methods [7, 10] mean each pixel is calculated through the mapping function to get new luminance value. An algorithm of contrast enhancement maintaining brightness based on the weighted sub-images proposed by Lv [11] is one of them. Although the contrast is enhanced not locally and detail losing avoided in this algorithm, it needs to estimate mapping parameters in advance. And it is difficult to produce better result when images are over or

under exposed. Another popular method is based on exposure [12, 13], mainly through adjusting luminance value of the pixel interesting targeted. The global color image enhancement algorithm based on retinex developed by Li [14] derived from this idea. It enhanced images by reflected information of objects features which is obtained through fast Gaussian filter and global γ transformation in HSL space, but it still causes the loss of detail information from the regions of high and low luminance.

For addressing the shortcomings discussed above, a novel multi-layer adaptive model is proposed in this paper to achieve optimized design for images in brightness discrimination, adaptive adjustment, etc. The algorithm includes the statistical distribution analysis, model parameters estimation and multi-layer model establishment. This paper is organized as follows. The framework structure of our approach is introduced briefly in Section II. Before detail explanation for utilizing multi-layer adaptive pre-processing model in Section IV, the preliminary work for panoramic images classification based on luminance is illustrated elaborately in Section III. Experiment results are shown in Section V, and we conclude our paper in Section VI.

II. OVERVIEW OF OUR APPROACH

It is often difficult or impossible to improve the large amount of panoramic sequence images relying on a single method. The proposed algorithm is depicted in Fig.1. As can be seen, brightness-based image classification is performed. Then multi-layer model that has been used to pre-process the images fast and efficiently will make them with character of vibrant colors, moderate brightness and obvious details. The final results are suitable for subsequent process and application.

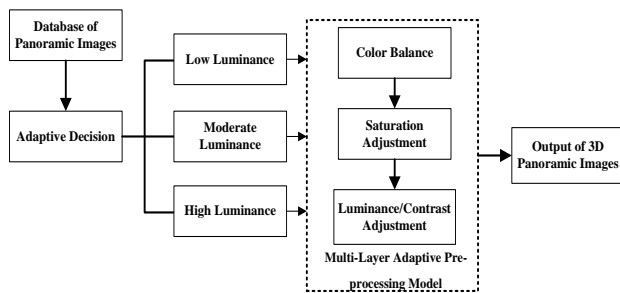


Figure1. Framework of adaptive preprocessing multi-layer model

III. LUMINANCE DISTRIBUTION

In order to obtain more accurate luminance distribution law of 3D panoramic sequences images and verify its better stability, we selected tens of thousands representative images from database of 3D panoramic images of the city of Suzhou as sample set X to test. The tested panoramic images derive from different time, locations, and weather conditions. For improving the real-time and accuracy of the algorithm, sample images form X should be greyed to get new sample set $Y\{y_1, y_2, y_3, \dots, y_n\}$ before preprocessing. $Y\{y_1, y_2, y_3, \dots, y_n\}$, where y_i ($i=1, 2, \dots, n$) is mean gray value of the panoramic image.

Here, Fig.2 (a) is the statistical distribution of sample set Y.

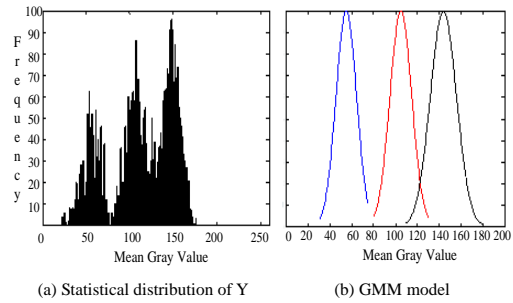


Figure2. Statistical distribution of Y and its GMM model

As seen in Fig.2 (a), there are three distinct peaks. Therefore, the panoramic images from sample set Y can be divided into three categories: low luminance, moderate luminance, high luminance. A significant watershed is existed at about 75(mean gray value) from Fig.2 (a). And, there is the only one independent peak that can be found between 25 and 75. Then known by Central-limit theorem, this independent peak between 25 and 75 can be considered approximately as the Gaussian distribution when the number of y_i distributed in 25-75 (mean gray value) increased. This can be described as follows,

$$\lim_{n \rightarrow \infty} P\left\{\frac{\sum_{i=1}^n \xi_i - n\mu}{\sqrt{n}\sigma} \leq x\right\} = \frac{1}{\sqrt{2\pi}} \int_{-\infty}^x e^{-\frac{t^2}{2}} dt = \phi(x) \quad (1)$$

suppose $\{\xi_i\}$ are independent and identically distributed, and $E\xi_i = \mu, D\xi_i = \sigma^2$ ($\sigma > 0$), $i=1, 2, \dots$ also exist.

Since,

$$\mu_1 \approx E(\xi_i) = \frac{1}{n} \sum_{i=1}^n \xi_i \quad (2)$$

$$\sigma_1^2 = D(\xi_i) = \frac{\sum_{i=1}^n (\xi_i - E(\xi_i))^2}{n}, \xi_i \in (25, 75) \quad (3)$$

The Gaussian distribution of low gray value for panoramic images is:

$$G_1(\xi) = \frac{1}{\sigma_1 \sqrt{2\pi}} e^{-\frac{(\xi - \mu_1)}{2\sigma_1^2}}, \xi \in (25, 75) \quad (4)$$

However, the distance between two peaks which belong to moderate luminance and high luminance in Fig.2 (a) is so close that the above method cannot provide a better approximation to the data distribution of multi-model. Thus, Gaussian Mixture Model (GMM) [15] is introduced to describe the changes of mean gray value greater than 75 for panoramic images. It shows that each mean gray value greater than 75 is described by K ($K=2$ in this paper) Gaussian distribution. GMM is shown in Fig.2 (b). Define ξ_i as the mean gray value for panoramic images in our paper, and its probability density function can be derived by K 3D Gaussian function:

$$P(\xi_i) = \sum_{n=1}^K \omega_{n,i} \times \eta_n(\xi_i, \mu_n, \sum n), \xi_i \in (75, 180) \quad (5)$$

where $\omega_{n,i}$ ($n=1, 2$) is the weight of mean gray value ξ_i ,

and $\sum_{n=1}^k \omega_{n,i} = 1$; $\eta_n(\xi_i, \mu_n, \sum n)$ is the PDF of SGM of n ; $\sum n$ is the variance of Gaussian distribution of n .

(μ_2, σ_2^2) and (μ_3, σ_3^2) can be quickly obtained by EM algorithm. So according to the optimal decision threshold criterion, the best decision threshold b^* is:

$$b^* = \frac{\mu_2 - \mu_1}{2\sigma^2} - \frac{\mu_2 + \mu_1}{2} \ln \frac{P(0)}{P(1)} \quad (6)$$

where, $P(0)$ and $P(1)$ represent the probability of appearing images with moderate luminance and high luminance respectively among TB level's database panoramic images, and they are empirical values extracted from long term shooting at various locations and large amounts of data statistics.

To simplify the calculation, suppose $\sigma_1^2 \approx \sigma_2^2 = \sigma$. With this, the panoramic images with moderate luminance or high in database can be correctly distinguished. Fig.3 is a flow diagram of classification system of image luminance.

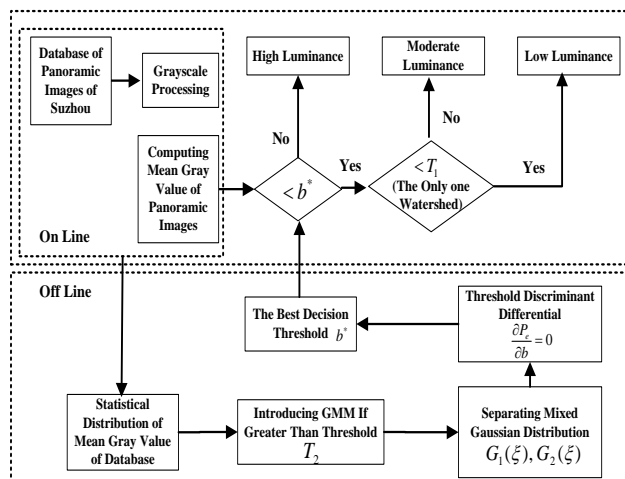


Figure3. Flow diagram of classification system of image luminance

IV. MULTI-LAYER ADAPTIVE PRE-PROCESSING MODEL

A. Adaptive Color Balance

Color balance is vital in image processing and editing. Pixels in RGB color space defined as additive color model should be mapped into CMYK space termed subtractive model to complete color balance. It is observed that the different combination of RGB components can produce any color in CYMK. Thus, all add-subtractive operations can be done directly in RGB space to improve the efficiency. Therefore, the traditional color balance algorithms relied on CMYK space is improved in our paper aimed at bettering processing efficiency at this step for panoramic images with different luminance level.

To control the proportion of three theoretical primaries, we introduce parameters $b_n \in (-50, 50)$, $n=1, 2, 3$. Here, b_n determines the tonal-ratio of the global image in RGB space. Specifically, b_1 determines the ratio of cyan-red color. If $b_1 > 0$, the red component of a panoramic image will increase; in other words, the cyan component

decreases, and vice versa. With the same effect, b_2 and b_3 denote the magenta-green and yellow-blue channel respectively. Empirically, the values of b_n depend on the luminance of panoramic images are given in Tab.1.

TABLE I.
VALUES OF b_n

	b_1	b_2	b_3
Low Luminance	5	5	3
Moderate Luminance	15	15	10
High Luminance	5	5	-5

The change Δ_m in RGB channels of each pixel $I(x, y)$ for the panoramic image can be described as:

$$\Delta_m = \begin{cases} 1.062 - \frac{1}{I_m(x, y) * 16} + 1, b_n > 0 \\ 1.075 - \frac{1}{(255 - I_m(x, y) * 16)} + 1, b_n < 0 \end{cases} \quad (7)$$

where $I_m(x, y)$ is RGB component of the pixel $I(x, y)$.

Thus, we compute the output of adaptive color balance by:

$$I_m(x, y) = I_m(x, y) + b_n * \Delta_m \quad (8)$$

Fig.4 shows the comparison between input and output images processed by (8). The real color of leaf or sky is not reflected in the input images influenced by lighting angles and environmental factors. Obviously, they are not suitable for subsequent Street View service. Thus, the color-ratio should be adjusted to meet visual effects. For example, the leaf lack vitality may look like more vivid by increasing b_2 appropriately, and the clear sky recovered from dusky one by adjusting b_3 may be more attracting. In addition, detail enhancement is realized through color balance adjustment.



(Left: before processing, Right: after processing)

Figure4. Results from adaptive color balance algorithm

B. Saturation Automatic Adjustment

The Street View captured outside is not saturated due to the limitations of cameras' quality and environment conditions, and these images should be adjusted correspondingly [7]. A commonly used method is to convert RGB color space to HSL space before adjusting S channel. However, the adjusted image is always stiff. Therefore, a semi-independent saturation adjustment algorithm is proposed in the paper. The output values are computed only in RGB color space just by analyzing the feature of S and L channel improving the efficiency.

By this way, we first get the corresponding matching adjusted parameter δ of saturation based on the luminance of panoramic images. Here, $\delta \in (-1, 1)$. Then the

corresponding values in S and L channel are used to ensure that images are not distortion. The explicitly expression is:

$$\delta' = \begin{cases} \frac{1}{s} - 1, & \delta > 0, \delta + S \geq 1 \\ \frac{1}{1-\delta} - 1, & \delta > 0, \delta + S < 1 \\ \delta, & \delta \leq 0 \end{cases} \quad (9)$$

Through δ' , each pixel can finally be automatically adjusted by:

$$I_m(x, y) = I_m(x, y) + (I_m(x, y) - L * 255) * \delta' \quad m \in (R, G, B) \quad (10)$$

The result by our algorithm is shown in Fig.5. To some extent, the saturation of an image can reflect its brightness. From the remarked red box in Fig.5, the brightness of images is significantly enhanced. For instance, the intrinsic color of cars has been fully reflected after processed. Although the same performance could be achieved through operating in HSL space, it will result in time-consuming. It's also important that automatically enhance the saturation of necessary parts while maintaining well-saturated parts (see the last image

in Fig.5: improving the saturation of background clouds, maintaining the color of branches closed to us).



(Left: before processing, Right: after processing)

Figure5. Results from saturation automatic adjustment

C. Adaptive Luminance/Contrast Adjustment

Luminance and contrast of the image have deep impact on human visual sensory. Appropriate adjustment may probably bring unexpected visual effects. The most popular method is forcing each pixel to make adjustment at the same degree [16]. Consequently, some heavy exposed regions of the image are brighter or even distorted if global adjustment algorithm be adopted. Obviously, the treatment is counter-productive, and is not expected to image's quality. Therefore, a novel local adjustment algorithm has been proposed in the paper to ensure that luminance adjustment is adaptive relying on the character in the local image. That means at lower luminance region, the brightness increase faster; at high luminance region, it is maintained. The specific algorithm process is presented in Fig.6.

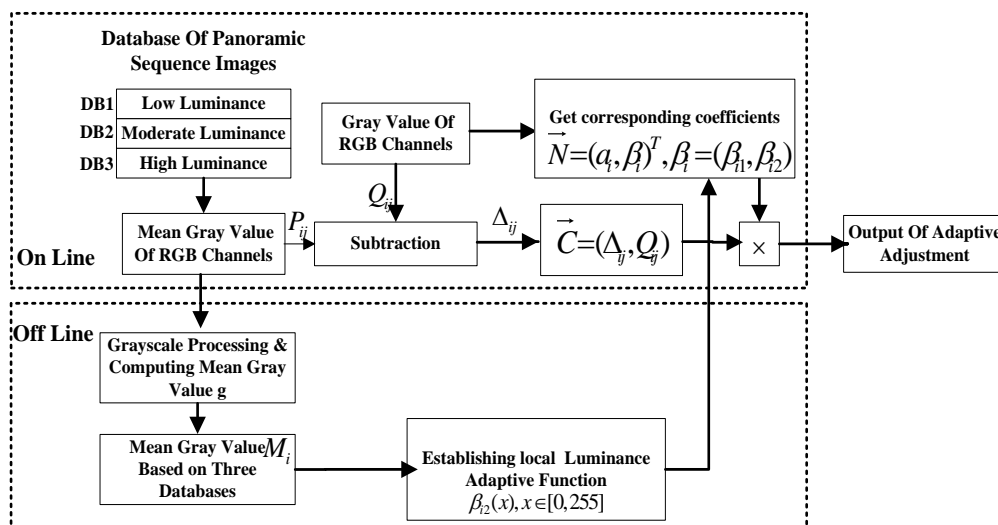


Figure6. Algorithm flow diagram of adaptive luminance/contrast adjustment

To better understand the algorithm, we define vectors:

$$\vec{N} = (\alpha_i, \beta_i)^T, \quad \vec{C} = (\Delta_{ij}, Q_{ij}) \quad (11)$$

where α_i is global adaptive coefficient for contrast, β_i is brightness adjustment coefficient, $i(i \in \{1,2,3\})$ represents the panoramic images of three luminance levels and Δ_{ij} is defined as:

$$\Delta_{ij} = Q_{ij} - P_{ij} \quad (12)$$

Here, Q_{ij} is the gray value of channel $j(j \in \{1,2,3\})$ for a pixel and P_{ij} is the mean gray value of channel j for the image.

To effectively realize local luminance adjustment for panoramic images, the brightness coefficient should be corrected:

$$\beta_i = (\beta_{i1}, \beta_{i2}) \quad (13)$$

where β_i includes two parts, β_{i1} denotes global brightness adjustment, and β_{i2} represents the fine-tuning coefficient for local adaptive brightness adjustment..

TABLE2. VALUES OF α_i, β_{i1}

	Low Luminance	Moderate Luminance	High Luminance
α_i	1.2	1.6	0.9
β_{i1}	1.2	1.4	0.9

It is easy to get the corresponding values of α_i and β_{i1} for images after right classification by luminance (see Tab.2). The forth-order nonlinear fitting function and LM algorithm [17], combining with RANSAC algorithm [18] to improve fitting accuracy, has been adopted to obtain β_{i2} .

Specifically, before setting up the functional projective relationship from $f_i(x, y)$ to β_{i2} , it is vital to compute mean gray value $M_i, i \in (1,2,3)$ of sample set Y based on three sub-databases classified by brightness.

According to the requirement of local luminance, $f_i(x, y)$ and β_{i2} , should meet the following conditions:

$$\begin{cases} \beta_{i2} > 1, & f_i(x, y) < M_i \\ \beta_{i2} < 1, & f_i(x, y) > M_i \\ \beta_{i2} \approx 1, & f_i(x, y) \approx M_i \end{cases} \quad (14)$$

For the sub-database of high luminance, maintain $\beta_{32}=1$ due to its heavy exposure.

Finally, make use of RANSAC algorithm to exclude individual points not matched with the actual model, and repeat iteration until getting optimized fitting functions to three kinds of panoramic images:

$$\beta_{i2}(f_i) = G_i(f_i(x, y)) \quad (15)$$

where, G_i is the nonlinear fitting operator. The result of fourth-order nonlinear fitting model is shown in Fig.7.

Thus, we obtain:

$$\begin{aligned} I_{ij}(x, y) &= \vec{C} \times \vec{N} = (\Delta_{ij}, Q_{ij}) \times \begin{pmatrix} a_i \\ \beta_i \end{pmatrix} \\ &= (\Delta_{ij}, Q_{ij}) \times \begin{pmatrix} a_i \\ (\beta_{i1}, \beta_{i2}) \end{pmatrix} \\ &= \Delta_{ij} * a_i + Q_{ij} * \beta_{i1} * \beta_{i2} \end{aligned} \quad (16)$$

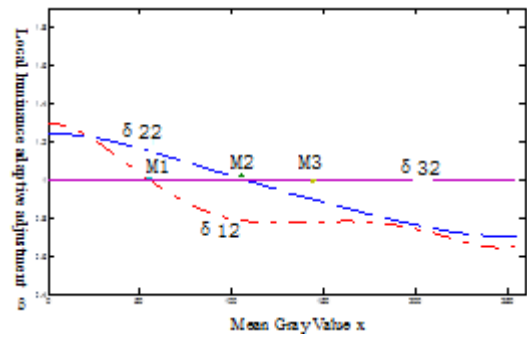


Figure7. Fitting curve of local adaptive luminance adjustment coefficient β_{i2}

where I_{ij} denotes the final output pixel (x, y) in the panoramic image.

V. EXPERIMENTAL RESULTS

An adaptive pre-processing system by C++ basing on the proposed algorithm is simulated. The system running on Core2 Duo T5870 processor, 1GB RAM, is applied to the pre-process three-dimensional panoramic sequence images with resolution of 5400*2700. Its average processing speed maintains at 15 Frames/min by testing database of Suzhou panoramic sequence images. Some representative images in Fig.8 to Fig.10 have been selected from database to analyze processing effects in detail. For the image of low luminance, brightness can be adaptively adjusted to improve the image quality by making use of β_{i2} which is obtained by optimized reiteration using LM algorithm. For example, in Fig.8 (a), maintaining the brightness of the sky and wall and increasing the luminance of billboards along the street are the most effective ways to pre-process low luminance image. And final processed result by our algorithm is shown in Fig. 8 (b).



Figure8. Pre-processed result for the low luminance image

Obvious detail enhancement can be observed in the given regions (Fig. 8 (c) to Fig. 8 (e)) marked by red box. The words written on the billboards in Fig.8 (c) and Fig.8 (d), such as “Yongzhu Cashmere” or “Jinteng real estate agent service”, can be seen clearly after pre-processing. And the model worn red knitwear in Fig. 8 (e) is more vivid than input image. The pre-processed result for the moderate panoramic image is shown in Fig. 9. As seen,

the objects in Fig. 9 (b), such as clear sky or green trees are more close to reality treated by our algorithm. The bush along the road seems covered with thick dust due to cameral imaging and illumination, losing its bright color in input image (Fig. 9 (d)). However, after appropriate processing, its real color is recovered, even meets human visual effects.

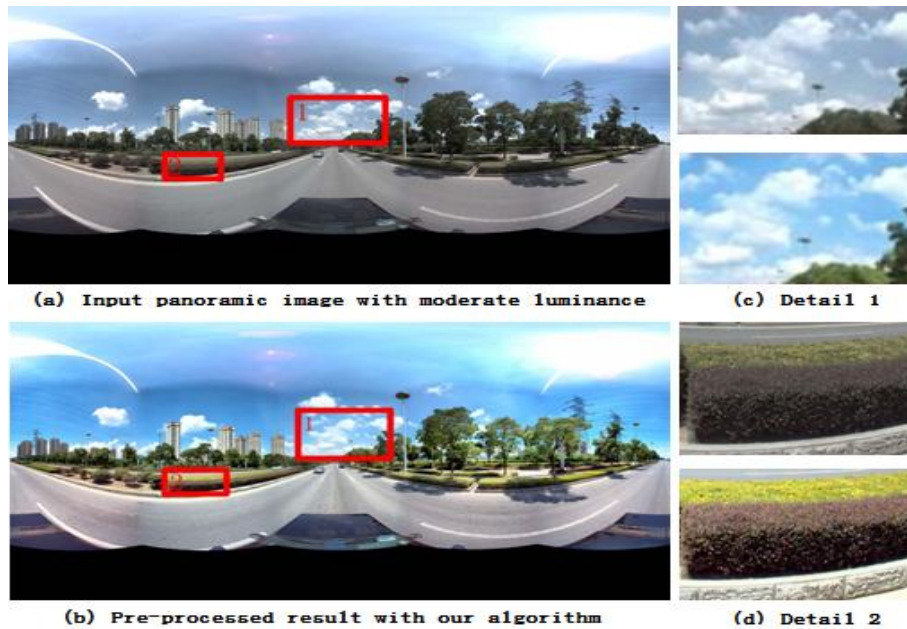


Figure9. Pre-processed result for the moderate luminance image

For the panoramic sequence images of high luminance, the mean gray value is maintained at approximately 140, or even higher, after grayscale processing, leading to obvious color distortion (see red box 1 in Fig. 10). The billboard presents dark red in red box 1. Nevertheless, its original color is red. In addition, the brightness of overall image (see Fig.10) is unevenly distributed due to directional cameras. Through nonlinear adjustment, the problem with uniformity of

brightness has been solved (see Fig. 10) and the man riding an electromobile in marked red box 2 is more visible after effective processing.

The above experiments show that the proposed algorithm can significantly adjust the luminance, chromaticity and contrast of 3D panoramic images even if unevenly distributed illumination caused by directional cameras.



Figure10. Pre-processed result for the high luminance image

VI. CONCLUSION

A novel multi-layer adaptive pre-processing model has been proposed in the paper based on detailed analyzing difficulties in the process of panoramic images pre-treatment. By introducing methods of statistical distribution, gaussian mixture model (GMM) and threshold decision, the panoramic sequence images can be effectively classified according to luminance. Then some important factors, such as luminance/contrast, saturation, color balance, have been considered to adaptively pre-process images to ensure the visual effects. At the same time, to make sure the robustness of model parameters, the improved RANSAC method and LM algorithm has been used. The system performs better in efficiency and robustness through a lot of tests based on database of Suzhou panoramic images. Since panoramic images wide application and street view popularization, we believe applying pre-processed panoramic images into street view will have promising market in the future. So we leave this for future studies.

ACKNOWLEDGMENT

The research was supported by a grant from Nature Foundation of Jiangsu Province (Project No. BK2012166), Natural Science Foundation of Jiangsu University (Project No.12KJB10031), Construction system of science and technology project of Jiangsu Province (Project No. JH21) and Open Foundation of Modern enterprise information application supporting software engineering technology R&D center of Jiangsu Province (SK201206).

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