Consistent Segmentation Based Color Correction for Coarsely Registered Images

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***Abstract*—Local color correction methods transfer colors between corresponding regions. However, inconsistent segmentation between the source image and the target image tends to degrade the correction result. In this paper, we propose a local color correction technique for coarsely registered images. In the segmentation step, it enforces the consistent segmentation on both source and target images to alleviate the inaccurate registration problem. In the color transfer step, it uses the region confidences and the bilateral-filter-like color influence maps to improve the color correction result. The experiment shows the proposed method achieves improved color correction results compared with the global methods and the recent local color correction methods.**

***Keywords*-consistent segmentation; color correction; conditional random fields;**

I. Introduction

The goal of image stitching is to register multiple images geometrically and photometrically. Compared to geometric registration, photometric registration has received relatively simpler treatment. However, overlapping images with perceptible color difference are inevitable in real world. One of the examples is Google Street View, which contains countless coarsely registered images with visually different colors (figure 5).

In this paper, we propose a local color correction technique for coarsely registered images with unknown caption condition, i.e., images can be taken at different time, different location or different cameras. Compared with state-of-the-art local color correction methods [1], [2], it obtains better results due to our consistent segmentation method which alleviates the negative effect rising from inaccurate registration, the bilateral-filter-like color influence map which avoids the color over-smoothing across regions and region confidences used to reject the inconsistent regions. We show the application on coarsely registered images acquired from Google Street View and achieve the best result compared to related state-of-the-art local color correction methods.

II. Related work

Wei and Mulligan [3] have given a unified evaluation of color correction technique in the context of automatic multi-view image and video stitching. Following this evaluation, [4] and [2], which have been widely used in color transfer research, are more suitable for the coarsely registered images. [2] could be the first option to try for general image color correction task.

Global color transfer method [4] linearly transfers the global color characteristics from the source image I^s to the target image I^t. The color transfer function is defined as:

$$\bar{I}_i^t = \mu^s + \frac{\sigma^s}{\sigma^t}\left(I_i^t - \mu^t\right) \tag{1}$$

where $\bar{I}_i^t$ and I_i^t are, respectively, the corrected and original values at pixel i of the target image. The (μ^p, σ^p) are the mean and standard deviation of the global color distribution and superscript $p \in \{s, t\}$ associates them with source or target image. However, inadequate consideration of color statistical information and spatial information tends to result in unsatisfying result.

According to the survey [3], local color correction approach [2] is recommended as the first option to try color correction for general images. They construct a probabilistic segmentation with the Gaussian Mixture Model (GMM) assumption. The final corrected color is the weighted version of global color transfer function (1). However, the assumption of GMM will restrict the flexibility of segmentation. Small region may not be properly segmented if they do not contain enough pixels to form a distinctive Gaussian component. Moreover, there is no guarantee that this algorithm will produce consistent segmentation.

Oliveira et al. [1] proposes another local color correction approach for the coarsely registered images. The target image is segmented and projected onto the source image using the inaccurate registration. The local color statistics are calculated for each region. Then Color Influence Maps (CIM), a weight mask measures the color similarity between pixels and color regions, are used to produce a smooth correction result [5]. The CIM is defined on the target image as $CIM_i^k = \exp\left(-3\|I_i^t - \mu_k^t\|^2\right)$, where μ_k^t is the mean of the region k. This approach was found to outperform [2] in terms of color similarity. However, this local approach is sensitive to inaccurate image registration which makes the segments of target images contain a large set of inconsistent colors. And the CIM tends to produce an over-smoothed result for the reason that it combines colors of the segments far away from the corrected pixel. Another problem may degrade the color correction result is that source and target

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images may contain inconsistent parts. For instance, a tree at the bottom left corner of the source image (figure 1(a)) does not exist in the target images (figure 1(b)). Apparently, the inconsistent regions should not transfer their colors into the other image.

In this paper, we propose an unsupervised local color correction method. The important advantages of our approach are: 1. We introduce a unsupervised consistent segmentation method to address the inaccurate registration problem, does not need any color distribution assumption. 2. We calculate the region confidences for each segment to rule out the inconsistent parts of the image pair. 3. In the color transfer step, we improve the CIM in [1] with spatial factor. The improved CIM can be considered as a superpixel bilateral filter and lead to a significant color correction improvement.

III. Approach overview

Our color correction technique focus on the coarsely registered images with unknown capture conditions. As there is no additional information such as pre-calibration information of radiance or strong geometric constraint from the multiview camera systems, the correction method can only rely on the colors of the images and coarsely registered geometric constraint. The proposed correction method involves four main steps: 1. The global color correction [4] is employed to obtain an initial correction result. This step makes source image and target image have the same mean and standard deviation of the global color distribution. Thus, the color difference between the corresponding pixels distributed in a reasonable range. 2. Consistent segmentation is applied on the coarsely registered image pair and region confidences are estimated. 3. The improved CIMs are computed. 4. The colors of the target image is corrected in $l\alpha\beta$ color space [6], using the consistent segmentation result and the improved CIMs.

IV. Consistent segmentation

Consistent segmentation means that if two pixels belong to the same segment in one image, then their (real) corresponding pixels in the other image also belong to the same segment (figure 1(a) and 1(b)). These two segments are called the segment/region correspondence. Local color correction implicitly assumes that segments between the image pairs are consistent. Therefore, non-consistent segmentation will affect the quality of the color correction result.

However, there is no straightforward method to achieve consistent segmentation on the source and target images. We cannot directly project the source image segments to the target image due to the inaccurate registration (figure 1(c)). If target image and source image are segmented independently, non-consistent segmentation result will be obtained due to the color difference (figure 1(d)). The challenge of our consistent segmentation problem is that the color similarity, a constraint widely used in lots of applications, cannot be used due to the color difference. In fact, if the corresponding parts of the images have similar colors, there would be many existing methods to achieve the consistent segmentation. However, the colors of the two images are usually different in the correction problem. In our consistent segmentation method, we make two assumptions as follows:

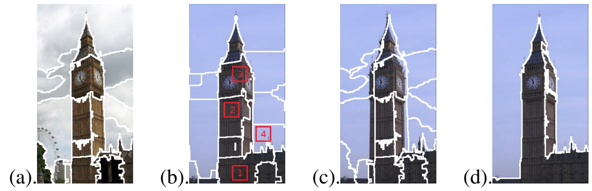


Figure 1. Consistent segmentation. (a), (b) are consistent segmented using our method, the number will be used to show the corresponding CIMs in figure 3. (c) directly uses the segmentation result of (a) and shows that coarse registration introduces inaccurate segmentation. (d) is independently segmented and non-consistent regions occur.

1. Although the colors between the source and target images are different, color difference of the most corresponding points varies in some narrow range (after global correction). Too large and too small color difference are all correspond to low probability. In our approach, we use the color difference distribution and color difference features to guide the consistent segmentation, which will be introduced in IV-A and IV-B respectively.

2. Coarse registration is an important spatial constraint. We assume that the position of the corresponding point should appears in the neary region. For notion clarity, we assume the target image has been resampled to the same size as the source image by using the inaccurate registration. Therefore, the pixel i in target image and pixel i in source image are inaccurate pixel correspondence induced by the inaccurate registration. It should be realized that the inaccurate pixel correspondence is not the real pixel correspondence. Hence, if pixel i belongs to the target image, its real corresponding pixel j in source image should be an element of the possible corresponding pixel set $K_w(i) = \{u \,|dist\,(u,i) \leq w\}$ in source image, where $dist$ is some metric defined over pixel set. In this paper, the possible corresponding pixel set $K_w\,(i)$ is a square window centered at pixel in source image with the window width $2w+1$. Thus, when we are assigning a region label to pixel i in target image, we only need to consider pixels in the possible corresponding pixel set $K_w\,(i)$, instead of the entire image.

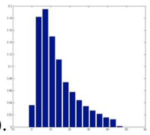
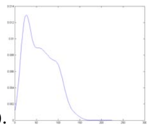
In our method, we initially use an unsupervised segmentation method, mean shift algorithm, to segment the source or target image. Each pixel i belongs to exactly one segment identified by its region variable $R_i^q = \{1, 2, ..., N\}$ and the superscript $q \in \{s, t\}$ associates it with source or target image. The k-th region is then simply the set of pixels P_k^q whose region-correspondence variable equals k, i.e., $P_k^q = \{i\,|R_i^q = k\}$.Without loss of generality, the source (a).  (b). 

Figure 2. Color difference distribution. (a) Total color difference histogram of 85 test image pairs. Most pixel colors vary in small range. (b) An example of region (not shown) color difference distribution estimated by the Pazen-window approach.

image is always assumed to be initially segmented. Then the target image is consistently segmented into corresponding regions according to the source image. This problem is formulated in a CRF framework and a detailed introduction is given in IV-C.

A. Color difference distribution

Since the color similarity constraint cannot be used in color correction, we use color difference distribution to describe the possibility of the pixel in target image corresponding to the pixel in the source image. The color difference is measured in Euclidian distance in $l\alpha\beta$ color space: $d(I_i, I_j) = \|I_i - I_j\|_2$ In order to show the characteristics of the color difference distribution, we firstly apply the global color correction method on 85 pairs of precisely registered images with different colors in the Middlebury Color Datasets. Then, we estimate the pixelwise color difference histogram (figure 2(a)). We can see that most colors vary in a narrow range, frome 0 to 40 with the peak at 9 in this case, and significant color difference corresponds to low probability. This is consistent with our color difference assumption.

However, in our application, we cannot get the accurate registration between the images. Thus, the inaccurate pixel correspondences are directly used to calculate the pixelwise color difference values $D_i = d\left(I_i^t, I_i^s\right)$ with the implicit assumption that the coarse registration error is relative small and the nearby pixels are likely to have similar colors.

We use the Pazen-window [7] approach to derive a nonparametric representation of the region color difference distribution for each region in source image (figure 2(b)). The region color difference distribution $\Pr_k^{re}(x)$ on region k is estimated using the region color difference set $S^k = \{D_i \,|i \in P_k^s\}$:

$$\Pr_k^{re}(x) = \frac{1}{|S^k|\, h} \sum_{i=1}^{|S^k|} K\left(\frac{x - S_i^k}{h}\right) \tag{2}$$

where the kernel function K is taken to be a Gaussian function. h is the bandwidth parameter.

The global color difference distribution $\Pr^{gl}(x)$ which uses all the data in color difference set D is also estimated and it will be used to estimate the region confidence for each consistent segment.

B. Color difference feature

We now describe how the color difference feature, used in color difference distribution, is calculated by the source image I^s, the target image I^t, the mean shift segmentation R^s of source image and the possible corresponding pixel set $K_w(i)$ which encodes the coarse registration constraint. The N-dimensional color difference feature ΔI_i is associated with pixel i in the target image. Its k-th component $\Delta I_i^k \in [0, +\infty)$ is the color difference between the pixel i and the average color of the pixels which are the intersection of possible corresponding pixel set $K_w(i)$ and the k-th region P_k^s:

$$\Delta I_i^k = \begin{cases} \left\| I_i^t - \dfrac{\sum\limits_{j \in K_w(i)} I_j^s \cdot \delta(R_j^s = k))}{\left|K_w(i) \cap P_k^s\right|} \right\|_2 & \text{if } K_w(i) \cap P_k^s \neq \phi \\ \infty & \text{otherwise} \end{cases} \tag{3}$$

where $\delta(\cdot)$ is the indicator function. Color difference feature ΔI_i^k combined with the corresponding region color difference distribution $\Pr_k^{re}(x)$ measures the possibility of the pixel i belongs to the region k. And it shows that it is almost impossible for pixel i in target image to take the region label k, if no pixel in $K_w(i)$ belongs to the region k in source image.

C. CRF model for consistent segmentation

We model the consistent segmentation problem in CRF framework [8]. The CRF energy function is formulated with a local color difference potential ψ_i and a pairwise edge potential ϕ_{ij}:

$$E\left(x \left| I^s, I^t, R^s\right.\right) = \sum_{i \in G} \psi_i\left(x_i | \Delta I_i, R^s\right) + \sum_{(i,j) \in E} \phi_{ij}\left(x_i, x_j | I_i^t, I_j^t\right) \tag{4}$$

where $G = (V, E)$ is a graph defined over the image with 4-connected neighborhood system. The discrete random field X is defined over the image pixel set $V = \{1, 2, ..., M\}$. Each random variable $X_i \in X$ is associated with a pixel $i \in V$ and takes a value from the label set $\Re = \{1, 2, ..., N\}$. R^s represents the segmentation on the source image and has been obtained by the mean shift algorithm. Any possible assignment of labels to the random variables $x \in \Re^N$ is a segmentation on the target image. ΔI_i is the N-dimensional color difference feature associated with the pixel i in target image. Consistent segmentation x^* on the target image can be solved by minimizing the CRF energy function above. As the pairwise potentials are of the form of a Potts model, this energy function can be minimized approximately using the α-expansion algorithm [9]. Some consistent segmentation results are shown in figure 4.

Local color difference potential. The local color difference potential ψ captures our assumption that color difference between the corresponding points should be in some reasonable range. It will give a large penalty on pixel correspondences with huge color difference. This potential is referred as local for the reason that it is conditioned on the segments of the images and it reflects the fact that different regions may have different color distortions. For instance, most times the sky in the photos is likely to remain in light blue while the color of the building may change relatively large due to the different illumination or different image color balance introduced by the camera. The local color difference potential ψ is defined as the negative logarithm of the local color difference distribution:

$$\psi_i\left(x_i|\Delta I_i, R^s\right) = -\log \Pr\left(x_i|\Delta I_i, R^s\right) \tag{5}$$

where $\Pr\left(x_i|\Delta I_i, R^s\right)$ is the conditional probability of x_i given corresponding color difference features ΔI_i and the segmentation R^s on source image. Using the Bayes' law:

$$\begin{aligned}\Pr\left(x_i|\Delta I_i, R^s\right) &= \frac{1}{Z}\Pr\left(\Delta I_i\left|x_i, R^s\right.\right)\Pr\left(x_i\left|R^s\right.\right)\\ &= \frac{1}{Z}\Pr_k^{re}\left(\Delta I_i^{x_i}\right)\Pr\left(x_i\left|R^s\right.\right)\end{aligned} \tag{6}$$

where Z is the normalization factor. The likehood term $\Pr\left(\Delta I_i\left|x_i, R^s\right.\right) = \Pr_k^{re}\left(\Delta I_i^{x_i}\right)$ is exactly the region color difference distribution estimated in IV-A. The prior term $\Pr\left(x_i\left|R^s\right.\right)$ is defined as:

$$\Pr\left(x_i\left|R^s\right.\right) = \begin{cases} \frac{1}{n} & \text{if } K_w\left(i\right)\cap P_{x_i}^s \neq \phi \\ 0 & \text{otherwise}\end{cases} \tag{7}$$

where n denotes the number of regions in the segmentation set $R^s_{K(i)}$. The prior term enforces a hard constraint that it is impossible for a pixel to take the region label which does not appear in the possible corresponding pixel set $K_w\left(i\right)$.

Edge potential. The pairwise edge potential, edge-sensitive smoothness prior, has the form of a contrast sensitive Potts model [10]:

$$\phi_{ij}\left(x_i, x_j|I_i^t, I_j^t\right) = \begin{cases} 0 & \text{if } x_i = x_j \\ \mathrm{g}\left(I_i^t, I_j^t\right) & \text{otherwise}\end{cases}$$

where the function $\mathrm{g}\left(I_i, I_j\right)$ is an edge feature based on the difference in colors of neighboring pixels. It is typically defined as:

$$\mathrm{g}\left(I_i, I_j\right) = \alpha_1 + \alpha_2 \exp\left(-\beta\|I_i - I_j\|^2\right)$$

where α_1 and α_2 are the weights assigning at each term. β usually takes the form $(2\left\langle\left\|I_i^t - I_j^t\right\|^2\right\rangle)^{-1}$, where $\langle\cdot\rangle$ means average over the image.

D. Region confidence

After consistent segmentation, corresponding segments can be obtained between the coarsely registered image pair. However, the image pair may contain the inconsistent parts such as a car appearing only in one image. In order to prevent the color of the inconsistent parts transferring to the other image, we use the global color difference distribution $\Pr^{gl}(x)$ as the measure of confidence of the segment correspondence obtained by the consistent segmentation. The confidence of the segment correspondence k is defined as: $C(k) = \Pr^{gl}\left(d\left(\mu_k^s, \mu_k^t\right)\right)$.

This measure will assign a low confidence if there exists a significant color difference between the region correspondences. As shown in figure 3(e), the dark segment in bottom left corner, which contains tree in source image, is assigned with a low confidence.

E. Parameter selection

Our consistent segmentation method involves three parameters: the window width w of the possible corresponding pixel set $K_w(i)$, the weight parameters α_1 and α_2 which encode the trade-off between the local color difference potential and edge potential. Large $\alpha_1$tends to suppress the small segmentation region, and large α_2 tends to cut the segmentation boundary at low gradient position [10]. Ideally, window width w should be equal to the max offset of the corresponding pixels. However, as the actual max offset is not known in the experiment images, w is set to be 3% of image width in all the experiment in this paper. The α_1 is set between 30 and 100 and α_2 between 0.1 and 10 in the experiment of this paper.

V. Local color transfer

The region correspondences are obtained after consistent segmentation. Then, Local color statistics (μ_k^p, σ_k^p), the mean and standard deviation of region k, can be estimated in each image $p \in \{s, t\}$. The local color correction can be applied by transferring the region color statistics from the source image to the corresponding region in the target image:

$$\bar{I}_i^t = \mu_k^s + \frac{\sigma_k^s}{\sigma_k^t}\left(I_i^t - \mu_k^t\right) \tag{8}$$

However, the color correction result is unnatural, especially at the boundary of the regions, by using the simple local transfer approach due to the complex color variation, imperfect consistent segmentation, etc. Hence, we improve the approach proposed in [1] to achieve the natural color transition across the region.

A. CIM with spatial factor

The CIM used in [1] only considers the color similarity factor and tends to produce over-smoothed result for the reason that every region in the target image will influence the color at pixel i. However, it makes little sense to combine colors far from the pixel i. Therefore, we add the spatial factor into the CIM and the improved CIM is defined as:

$$\overline{CIM}_i^k = \exp\left(-\frac{\|I_i^t - \mu_k^t\|^2}{2\alpha^2}\right)\exp\left(-\frac{dist_{re}(i, P_k^t)^2}{2\beta^2}\right) \tag{9}$$

where the distance between a pixel i to a pixel set $P \subset V$ is defined as $dist_{re}\left(i, P\right) = \inf\limits_{j\in P} dist\left(i, j\right)$. α and β are the

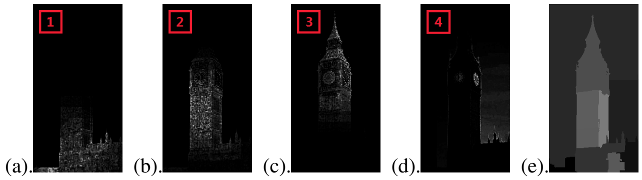


Figure 3. (a)-(d) Visualization of the improved CIMs of four segments. Distance factor reduces weights of the far away pixels. Darker colors mean lower contribution and each segment has high contribution at the nearby region. (e) Confidence map. Dark color means low confidence. The inconsistent segment correspondence at the bottom left corner which contains tress in source image is assigned a significant low confidence.

range and spatial bandwidth parameters, respectively. In the experiment of this paper, the α is set between 20 and 40 and the β is set to be 10% of the image width.

B. Weighted color correction with confidence

In order to prevent the colors of inconsistent segments from transferring into the target image, the region confidence is used to reject the low confidence segments in the color transferring process. Finally, our color correction function is the weighed version of the color transfer function (1). It is composed of the local color statistics obtained from the consistent segmentation, the improved CIMs and region confidences:

$$\bar{I}_i^t = \frac{\sum\limits_{k=1}^{N} \left(\mu_k^s + \frac{\sigma_k^s}{\sigma_k^t}\left(I_i^t - \mu_k^t\right)\right) \times \overline{CIM}_i^k \times 1[C(k) > \varepsilon]}{\sum\limits_{k=1}^{N} \overline{CIM}_i^k \times 1[C(k) > \varepsilon]} \tag{10}$$

where $1[x > \varepsilon]$ is the threshold function, equal to 1 when $x > \varepsilon$, and 0 otherwise. In the experiments ε is set to be 0.5%.

VI. Results and discussions

We compare our method with the global approach (GL) [4], probabilistic segmentation local color correction approach (PL) [2] recommended in the literature [3] and the recent unsupervised local color correction approach (UL) [1] which outperforms other local approach in terms of color similarity. Coarsely registered real world images are obtained from the Google Street View. 5 image pairs are the same scenes used in [1]. As it is hard to get the real pixel correspondences to measure the exact correction results, We use the same metric proposed in [1] which measures the improvement ratio of color correction method

$$CC_{method} = \frac{CS_{base} - CS_{method}}{CS_{base}} \times 100 \tag{11}$$

where $method \in \{GL,\ UL,\ PL,\ Pr1,\ Pr2\}$, the values respectively represent GL, UL, PL, proposed method without distance factor in CIM and the proposed method. Color similarity (CS) is defined as the three channel Euclidian distance between source image and the input image $CS = \left\| I_i^s - I_i^{input} \right\|$. The CS_{base} denotes the original color similarity between the target image and source image. CS_{method} denotes the final color similarity between the corrected image and the source image. Therefore, larger improvement ratio CC_{method} represents the better correction result.

Table I lists the improvement ratios of the color correction results. Scene#1 - #5 are the same images used in [1] and Scene#6 - #10 are some images selected from Google Street View. In order to show the importance of the improved CIM, we also run our method using the simple CIM without distance factor. We can see that the proposed method achieves the highest improvement ratio. The UL method performs better than the PL method in most cases. It also shows the effectiveness of the improved CIM. If we use the CIM without distance factor, the performance of the proposed method goes down in some of the images.

Figure 5 shows the color correction results of Scene#1, #2, #3, #9, and #10. From top to bottom, the images are the uncorrected image, correction with GL method, correction with PL method, correction with UL method, correction with proposed method and ground truth image. It shows that the UL method and our method obtain better visual results. The GL method does not perform well in the images contain huge variety of colors, as in Scene#3 and #10. In Scene#9, our method is more natural at the boundary region for the sake of the local properties of the improved CIM. In Scene#2, our method achieves better performance than UL method for the reason that UL method transfers the red color of the bridge into the sea with the problem of inaccurate registration. And our method also performs better in the sky by using the improved CIM which reduces blue color transfered from the sea.

We implemented our method using Matlab 7.7.0, and directly used the mean shift algorithm from [11] and α-expansion algorithm from [9]. Our unoptimized code totally spent 6 min for a 780 by 520 image pairs on an i3 2.27GHz laptop, about 4.5 min for the mean shift algorithm and 2.5 min for the consistent segmentation and local color transfer, while the local EM based algorithm from [3] requires about 10 min. Our method can be directly accelerated by replacing the mean shift algorithm with some other more efficient segmentation algorithms. Our method is slower than [1], but it has better correction performance.

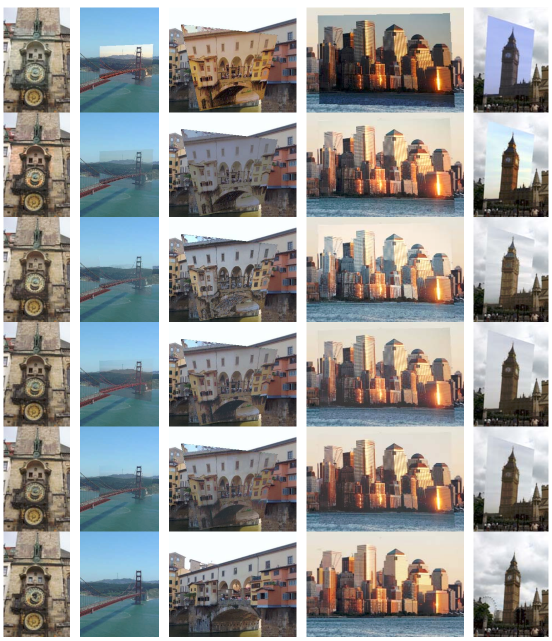
VII. Conclusion

This paper proposes a local color correction method for coarsely registered images. The experiment result shows that our local color correction method achieves the best performance among the recent local color correction approaches. In our approach, a consistent segmentation method is developed to alleviate the inaccurate registration problem.

Figure 4. Consistent segmentation on real world images. The left image is source image and the right image is target image.

Scene#	CC_{GL}	CC_{PL}	CC_{UL}	CC_{Pr1}	CC_{Pr2}
1	3.1	6.5	10.0	9.2	10.3
2	33.5	23.1	38.6	39.8	41.4
3	16.7	8.88	18.2	18.7	22.0
4	63.2	64.8	64.4	64.8	65.5
5	3.6	7.0	14.7	15.3	18.8
6	25.6	14.5	34.6	34.7	39.9
7	26.1	19.9	32.9	32.4	41.0
8	36.8	32.5	36.2	36.3	50.2
9	40.9	21.1	43.8	41.2	44.3
10	-2.2	12.9	12.1	13.7	14.3

Table I
IMPROVEMENT RATIOS OF THE REAL WORLD IMAGES.



(#1) (#2) (#3) (#9) (#10)

Figure 5. Some of correction results of registered real images. From top to bottom, the images are the uncorrected image, correction with GL method, correction with PL method, correction with UL method, correction with proposed method and ground truth image. Scene#1 - #3 are images used in [1]. Scene#9 and #10 are other images selected from Google Street View.

And the bilateral-filter-like color influence map is used to reduce the over-smoothing effect. Furthermore, this method can be easily extended to transfer colors to non-overlapped regions.

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