ROBUST COLOR CORRECTION IN STEREO VISION

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ABSTRACT

The phenomenon of color discrepancy between image pairs happens frequently in stereo vision systems. This inconsistence in color domain may cause difficulties when identifying point correspondence to reconstruct the scene depth. In this paper, we propose a robust algorithm to correct the color discrepancy between images. The proposed algorithm neither requires a color calibration chart/object which is a tedious procedure, nor explicitly compensates for the image as a whole, which possibly give bad correction results in local areas of an image. Instead, we correct the image region by region. Experiments show that the presented color correction algorithm is effective and efficient.

Index Terms— Color correction, stereo vision, SIFT

1. INTRODUCTION

The problem of color correction arises frequently in stereo vision because of the existence of color discrepancy between images. This is mainly due to the inconsistent parameters of camera devices and various lighting conditions from different viewpoints. If the problem is not well solved, the derived luminance and chrominance dissimilarities may severely affect the results of subsequent post-processing relying on color correspondence. For example, the color discrepancy between images may lead to false matched points, which will further results in unreliable reconstructed depth information.

Many algorithms have been proposed to address this problem, a review of which can be found in [1]. Basically, color correction in such applications can be done either by calibrating the camera parameters or by processing the images after acquisition [2]. Most algorithms from the first category employ a standard color calibration chart or object as reference to fulfill the task. Though it is a feasible solution, it is inconvenient to us in practice and works well only in indoor environment. Once the imaging condition changes, the whole tedious procedure has to be repeated. The second category usually corrects the image in a global manner. Images are treated as a whole and corrected by finding a color transfer function or mapping table. However, global correction does not necessarily meet the needs of local areas since different objects in the scene have different reflection and imaging models, which puts requirements for a more deliberate correction.

Although there are several existing local approaches [3, 5], they have their own shortcomings. [3] employs the PCA based method to correct the local region. However, it only utilizes the principal components. The remaining information omitted may cause deviation from the desired color correction. [5] models the image with GMM, but sometimes the assumption for local regions as Gaussian distribution is not true.

In this paper, we propose a local color correction algorithm based on our previous work [4, 9, 11]. The presented algorithm is robust and easy to use. Though we formulate the algorithm in the context of stereo vision, it can be extended to other applications such as artistic effect enhancement and image stitching in a straightforward way.

The rest of this paper is organized as follows. Section 2 describes the proposed algorithm. Section 3 shows the experiments we have done and Section 4 concludes the paper.

2. ALGORITHM DESCRIPTION

Since there are many sophisticated techniques [6] for geometrical calibration in stereo vision, we assume the input image pair in our algorithm is geometrically well calibrated. There are only horizontal displacement and color difference between the images. For convenience, the two images are respectively named as reference image and target image. Our goal is to correct the target image so that it resembles the reference one in color appearance. A flowchart of the proposed algorithm is shown in Fig. 1 and the detailed explanation is as follows.

(1) Extract SIFT keypoints from input images. Since SIFT keypoints [8] is robust to illumination change and addition of noise, many keypoints can be extracted from both images, which are proved to be enough in our latter processing.

(2) Find the corresponding keypoints. After keypoint extraction, we will find the matched pairs between the two

images. Original SIFT matching algorithm achieves this through an exhaustive search. However, that's time-consuming and of low efficiency. In our algorithm, we first calculate the optical flow of each keypoint in the target image, according to which its roughly estimated potential match can be identified in the reference image. Here the Horn-Schunks algorithm [10] is employed to compute the optical flow, which is based on the assumption of Eq. (1).

$$\frac{\partial E}{\partial x}\frac{\mathrm{d}x}{\mathrm{d}t}+\frac{\partial E}{\partial \mathrm{y}}\frac{\mathrm{d}y}{\mathrm{d}t}+\frac{\partial E}{\partial t}=0 \qquad (1)$$

Then the subsequent search for an accurate match is restricted to a rectangle window centered at the estimated point. Considering the specific application of stereo vision, we will add two restrictions to the searching process, the relaxed epipolar constraint and maximum displacement constraint [9]. We name this process as OF-SIFT and it can not only find more accurate matched points but also save more processing time (at least 97%). For more detailed discussion about OF-SIFT, such as the selection of searching window size, we can refer to [9].

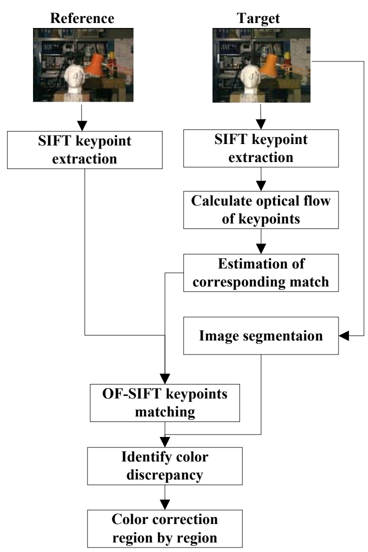


Fig. 1. Flowchart of the proposed algorithm.

(3) Segment the target image to get divided regions. To do color correction in a local manner, we also need to segment the target image into regions with similar colors and textures. Here the mean-shift algorithm [7] is employed because it is one of the best ranked segmentation algorithms according to our previous work on segmentation algorithm evaluation [11]. The following color correction is performed by regions acquired at this step.

(4) Local color correction. The color correction value of a particular region in the target image is inferred from the keypoints within it and its corresponding matches in the reference image. For a given region in the target image, the corrected value is calculated by averaging the color difference between all keypoints within it and their corresponding matches in the reference image. The following equation expresses this criterion,

$$C_{new}(i,j)=C_{old}(i,j)+\left(\sum_{x_t\in S}\left[CN(x_r)-CN(x_t)\right]\right)\Big/ keyNumInS \qquad (2)$$

where (i,j) is a pixel of region S in the target image, $C_{old}(i,j)$ is the value of (i,j) before correction for color component C (C can be H, S or I), and $C_{new}(i,j)$ is the corresponding value after correction of $C_{old}(i,j)$, x_t is a SIFT keypoint in region S, x_r is its corresponding match in the reference image, $keyNumInS$ is the number of keypoints in region S, and $CN(x_t)$ and $CN(x_r)$ are the mean color values averaged by 3×3 neighbors of x_t and x_r respectively.

However, if there are no SIFT keypoints within it (this is generally the case because SIFT keypoints are sparsely distributed), several keypoints should be added to the region. In this step we add the keypoints in a more prudent manner than [4]. Fig. 2 illustrates our method. If we add the keypoints M0-M4 for the shaded region ABCD according to [4], M3 will fall outside the region if the region is a concave one. Therefore, every time we add a keypoint, it will be checked whether its position is appropriate or illegal. Once the added point lies out of the region, we will replace the keypoint by adding other ones. Take M3 for example. If M3 does not lie in the shadow region, we can replace M3 by another point, named M3', that dichotomizes the segment M0M3 or any segment quartered by the five keypoints such as M0M1.

After adding keypoints successfully, their matches in the reference image are obtained according to the nearest matched pair outside the region (KR and KL in Fig. 2) and their relative position to M0-M4 [4]. The subsequent correction is the same as regions having keypoints within them.

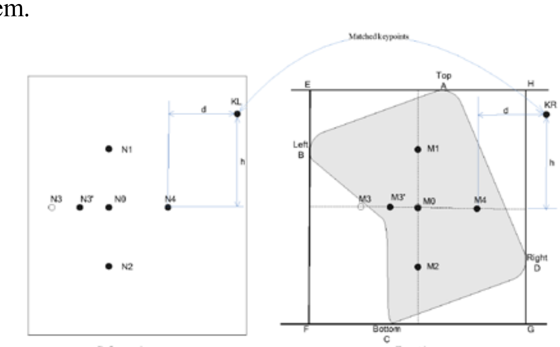


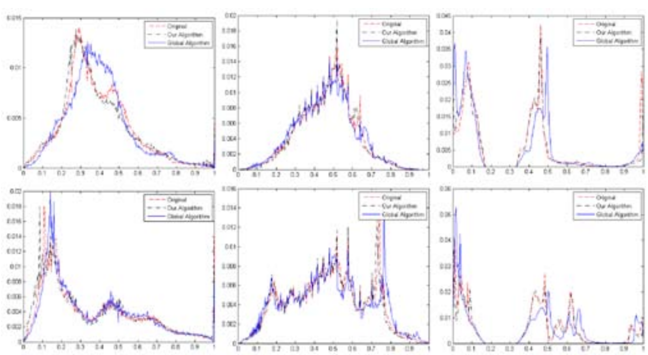
Fig. 2. Illustration of how to add keypoints.

3. EXPERIMENTS

In this Section, we have done experiments to prove the effectiveness of the proposed algorithm. Experimental images are from the well-known Middlebury website [13], which is a publicly available dataset for stereo vision research with all together 38 groups of images. Each group has a sequence of 7-9 standard stereo images with only horizontal displacement in position and two of them are provided with the ground-truth disparity map. We select the two images in each group with ground-truth disparity map to be involved in our experiments. Then for each pair, one image (target image) is adjusted by Photoshop software to be different from the other (reference image) in color appearance. Different regions of the image have different adjustments for each HSI color channel. The maximum adjustment from the original color value is up to 25%. Our aim is to correct the target image so that it looks the same with the reference one. The reason for selecting input images in such a way is that images from Middlebury dataset have standard known information, with which we can compare our experimental results to give a quantitative evaluation. This makes our conclusion more convincing.

Reference image   Target image   Our algorithm   Global algorithm

Fig. 3. Color correction results of the proposed algorithm.

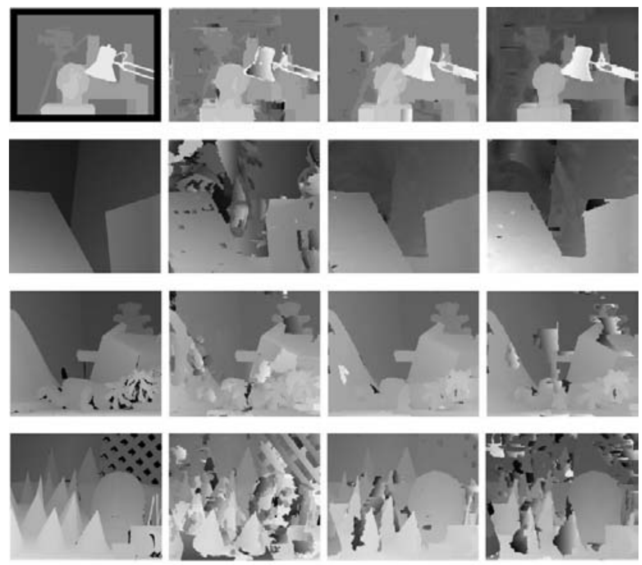


H channel   S channel   I channel

Fig. 4. Histogram comparison of different color channels for Venus (the first row) and Tsukuba (the second row) images.

We also do the color correction work with a global algorithm [12] and compare ours with it. For the consideration of limited paper length, the following shows the experimental results of only four most widely used images in stereo vision field. They are respectively Tsukuba, Venus, Teddy and Cones. From Fig. 3, we can see that there exists color difference between the reference and target images. Furthermore, since different regions of one image are adjusted differently, their color discrepancies are not the same. In this situation, existing global algorithms cannot give a satisfying result. But after correction of our algorithm, the result images look nearly the same as the reference one.

In order to evaluate the result qualitatively, we get the statistics of the image pixels and draw the histogram envelops for each color channel. The range of the three horizontal axes is scaled to [0, 1] and that of the vertical axes is normalized by the total pixel number of the image. Obviously from Fig. 4 we can find that, histograms of our algorithm have a greater resemblance with the original one than that of the global algorithm after color correction.



Ground-truth   Before correction   Our algorithm   Global algorithm

Fig. 5. Disparity maps before and after color correction of the target image.

Table 1 Comparison of error rates before and after color correction.

Images	Error rates of disparity computation (%)	
	Before correction	After correction (our/global algorithm)
Tsukuba	12.37	6.11 / 8.55
Venus	44.64	3.98 / 7.59
Teddy	35.26	14.43 / 28.25
Cones	64.90	22.69 / 44.13

To evaluate the results in stereo vision application, we use the image pairs before and after correction separately as inputs to calculate the disparity map with one of the highest ranked stereo matching algorithm [14] on Middlebury website. Then the acquired results are compared with the ground-truth ones to test the effect of the algorithm. We can find from Fig. 5 and Table 1 that if the input stereo images have great color discrepancy, the reconstructed disparity maps are of far lower quality and higher error rates than the ground-truth ones. After color correction, the results have been improved a lot and it is evident that our algorithm outperforms the global one. It also reveals a fact that even with one of the best stereo matching algorithms, it cannot handle the problem of color difference between stereo images. This makes it essential for the color correction process.

Fig. 6. Color correction results under extreme conditions.

Fig. 7. Color correction results of a real scene.

In order to prove the robustness, experiments under extreme conditions have been done. The maximum adjustment for each image in color value is up to 80%. Fig. 6 displays the results. We can see that there are apparent differences between the reference and target images. But after correction, the color resemblance has been improved a lot. Obviously, our algorithm performs much better than the global one. However, there are still small regions not calibrated well enough. This is because though our matching process can restrain some false matches basically, it cannot eradicate them from happening. As a result, if there exist false matched SIFT keypoints in a region, the color correction results may not be satisfying.

All the above experiments are conducted based on the Middlebury dataset. Here, we present the results on a real world scene. FinePix S5000 stereo cameras with different parameter settings and viewpoints are used to take pictures of a scene. The obtained image pairs have color difference. But after our calibration process, their color consistency is improved a lot. Our algorithm still outperforms the global one. Fig. 7 shows the results.

4. CONCLUSION

In this paper, we propose an algorithm for color correction that is proved to be robust, effective and simple to use. Though we formulate it in the context of stereo vision, it can be extended to other applications easily. Future work should pay much effort on how to get more reliable matched keypoints and get more accurate correction.

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