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Color Correction for Onboard Multi-camera Systems using 3D Gaussian Mixture Models

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Abstract— **The current paper proposes a novel color correction approach for onboard multi-camera systems. It works by segmenting the given images into several regions. A probabilistic segmentation framework, using 3D Gaussian Mixture Models, is proposed. Regions are used to compute local color correction functions, which are then combined to obtain the final corrected image. An image data set of road scenarios is used to establish a performance comparison of the proposed method with other seven well known color correction algorithms. Results show that the proposed approach is the highest scoring color correction method. Also, the proposed single step 3D color space probabilistic segmentation reduces processing time over similar approaches.**

I. INTRODUCTION

In recent years, vision based sensors have been increasingly applied to autonomous vehicles and advanced driver assistance systems. They have key advantages over some other sensors, such as: being passive, obtaining vast amounts of information and being a low cost technology. Actually, the low cost and the impossibility to get a good view of the entire road around the vehicle using a single sensor, leads to the use of two or more of these devices. Many examples can be given, from the DARPA Challenge competitors (*www.darpa.mil/grandchallenge*).

The usage of more than one camera onboard of a moving platform poses new problems, which have not yet received enough attention from the research community. In fact, no assumptions can be made on key parameters, for example, scene illumination and contrast, which are directly measured by the vision sensor. If images from the cameras are to be merged into a mosaic or analyzed by some feature extractor algorithm, colors in both images should appear similar. This problem, called the photometrical correspondence between images, has been addressed both by the computer graphics and the computer vision research communities.

The general problem of compensating the photometrical disparities between two coarsely geometrically registered images is referred to as color correction. This process is performed through the use of one or several *color transfer functions* that use an image as a reference. In other words, color correction is the problem of adjusting the color palette of an image using information from the color palette of another image. The image that is used as a reference is referred to as the *source image*, while the image which is going to be adjusted is called the *target image*.

Although many different algorithms have been proposed to perform color correction, no study has been published regarding the application of these algorithms to the vision sensors onboard autonomous vehicles. There are some characteristics in this particular application that make a specialized study necessary: real time requirements, since the processing time is coupled with the maximum vehicle speed; and the need to handle a great range of illumination conditions due to sun glare, tunnels, night or fog.

Some authors have suggested non parametric approaches to color correction, i.e., the methods make no assumptions about the nature of the color distribution. For instance in [1], color correction is done through the estimation of global and local color transfer functions. The complex estimation problem is reduced to a robust 2D tensor voting in the corresponding voting spaces. A cumulative histogram matching technique was presented in [2], while in [3] the entire probability density function is mapped without making assumptions on its nature. On the other hand, model based parametric approaches try to model the color distribution in the images and use tools that transfer the color distribution characteristics from one image to the other. One of the most important works in this scope is [4]. In this paper, a simple statistical distribution transfer methodology was proposed. It was also in [4] that alternative color models, namely the $l\alpha\beta$ color-space, where proved to be more effective for calculating the color transfer functions than the usual RGB color-space. It is successfully employed since it minimizes the cross channel correlation, which is present on many color spaces. This work has been extended in [5], where tools that permitted RGB color space to be used with similar effectiveness where presented. Principal component analysis where implemented by [6], and in [7] a gain compensation algorithm and a multiband blending post processing was proposed.

Indeed, the application of vision sensors to moving vehicles, especially the use of more than one camera, causes the images of these cameras to have different colors (Fig. 1, *left*). In order to process the set of images, color miss-balances must be compensated by means of some color correction algorithm.

In Section 2 a new color correction technique based on 3D Gaussian Mixture Models (*3DGMM*) is proposed. Results

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Fig. 1. The Atlascar robotic platform with several onboard cameras (*top*) (http://atlas.web.ua.pt). Onboard images taken with two cameras from a typical road scene. Source image (*bottom-left-top*), Target image(*bottom-left-bottom*); the mosaic of both which shows a clear difference in colors (*bottom-right*); .

are presented in Section 3, where the best ranked color correction algorithms in a recent performance evaluation for image stitching [8] are compared with the proposed approach. Conclusions are presented in Section 4.

II. Proposed Approach

The approach presented in [4] assumes a Gaussian distribution of color on both the source and target images, i.e., it uses a linear color transfer function. The Gaussian distribution based color transfer scheme, initially proposed in [4], can be defined as follows: let μ_s and μ_t be the mean color of the source and target images, while σ_s and σ_t are the standard deviations of those images. Then, the corrected image's color is given by the following Gaussian distribution transfer function:

$$T^{'}(\mathbf{x}) = \mu_s + \frac{\sigma_s}{\sigma_t} \times (T(\mathbf{x}) - \mu_t), \qquad (1)$$

where $T^{'}(\mathbf{x})$ and $T(\mathbf{x})$ are the target image's original and new single channel color, at pixel position $\mathbf{x} = [i, j]$, respectively. Equation (1) may be used to process single channel images (*gain compensation*) or color images (*color correction*). However, in practical situations, the color distribution of the whole image is seldom a normal distribution. Global modelling of the color distribution fails in practice because it provides only a rough approximation of the color distribution. By computing for several regions, a local color transfer function and assuming a separate Gaussian distribution for each, the set of color transfer functions will provide a more consistent color correction output. This was proposed in [9], where the Reinhard's methodology was extended to the local scenario, namely through a color transfer scheme based on single channel probabilistic segmentation and region mapping using the EM algorithm.

The current paper proposes to represent color distribution using *3DGMM* for joint probabilistic segmentation of the three color channels. Then, several color transfer functions can be derived from the adaptation of equation (1).

A. Probabilistic Segmentation with 3DGMMs

The segmentation step is intended to cluster the image into a set of colors. The assumption is that it is more feasible to represent color distribution as a Gaussian distribution in regions where only one color (or a more uniform set of colors) exist. The segmentation is done using *Matlab*'s *gmdistribution* toolbox. It is done by defining the same number of Gaussian clusters *NG* both for the target and source images. This is done under the reasonable assumption that, since the images have the same view of the scene, they both should have the same number of colors in the overlapping regions. After the segmentation, each pixel in the image is assigned a probability of belonging to Gaussian k, defined as: let the symbols μ^k and σ^k be the vector containing the three channel mean and standard deviations of region k of the image, while $\mathtt{I}(\mathbf{x})$ represents the three channel color of pixel $\mathbf{x}$. For a given region k, the Probability vector $\mathbf{P}^k(\mathbf{x})$ can thus be defined as:

$$\mathbf{P}^k(\mathbf{x}) = \frac{\exp\left(-\frac{(\mathtt{I}(\mathbf{x})-\mu^k)^2}{2(\sigma^k)^2}\right)}{\sum_{i=1}^{NG}\exp\left(-\frac{(\mathtt{I}(\mathbf{x})-\mu^k))^2}{2(\sigma^i)^2}\right)}, \qquad (2)$$

and the final probability of pixel $\mathbf{x}$ belonging to cluster k, a scalar denoted as $P^k(\mathbf{x})$, is given by the average of the three channel probabilities of $\mathbf{P}^k(\mathbf{x})$.

In [9], each channel of the image undergoes a segmentation procedure similar to this one. However, as will be shown in Section 3, by performing a 3DGMM of all three image channels in a joint segmentation step we are able to improve the color correction performance and reduce processing time.

B. Color Transfer Functions

The current paper proposes to perform a probabilistic segmentation of both the source and target images using 3DGMMs. The result of the segmentation step is that both the target and the source images are segmented into *NG* clusters, each representing a Gaussian for the inferred mixture model. When spatial information exists, which is the case since images are coarsely registered, the matching is performed based on the maximum correlation of pixel probabilities. Let $m(k)$ be the matching function that outputs the index of the source Gaussian for target Gaussian k:

$$m(k) = argmax(r(k,j)), \forall j \in \{1,2,3,...,NG\}, \qquad (3)$$

where r represents the correlation between the probabilities of target image Gaussians P_t with source image Gaussians P_s, given by:

$$r(k,j) = \frac{\sum_{\mathbf{x}=[1,1]}^{[W,H]} (P_t^k(\mathbf{x}) - \bar{P}_t^k) \times (P_s^j(\mathbf{x}) - \bar{P}_s^j)}{\sqrt{\sum_{\mathbf{x}=[1,1]}^{[W,H]}\left(P_t^k(\mathbf{x}) - \bar{P}_t^k\right)^2 \sum_{\mathbf{x}=[1,1]}^{[W,H]}\left(P_s^j(\mathbf{x}) - \bar{P}_s^j\right)^2}}, \qquad (4)$$

where $\bar{P}^k$ represents the average of probabilities for Gaussian k, and W, H are the image's width and height respectively.

The color correction procedure will make use of *NG* color transfer functions, each one corresponding to a match between a region in the target with a region in the source image. The color transfer functions ($\mathtt{ctf}$) are obtained by adapting (1) to the 3D case:

$$\mathtt{ctf}(k,m(k)) = \mu_s^{m(k)} + \frac{\sigma_s^{m(k)}}{\sigma_t^k} \times (\mathbf{T}(\mathbf{x}) - \mu_t^k), \qquad (5)$$

where $\mathbf{T}$ is a vector that denotes the three channels of the image.

C. Color Correction

Once the source and target images have been segmented into *NG* regions and the corresponding color transfer functions for each match are computed, the objective at this last stage is to correct the color of every single pixel. Because of the probabilistic nature of the proposed color segmentation, pixels may have non zero probability of belonging to more than one regions. Hence, the proposed color transfer methodology is defined as a weighted combination of all the computed color transfer functions:

$$\mathbf{T}'(\mathbf{x}) = \sum_{k=1}^{NG} P_t^k(\mathbf{x}) \cdot \mathtt{ctf}(k,m(k)), \qquad (6)$$

where the bold symbol $\mathbf{T}'$ denotes the three channel color of the corrected image.

III. Results

In order to test the proposed algorithm, the ATLASCAR robotic platform (http://atlas.web.ua.pt) [11] was used to acquire several images of typical road scenarios. The vehicle is used for research on autonomous driving and advanced driver assistance systems and it is equipped with several cameras (Fig. 1(*top*)). Although many video streams from the ATLASCAR were tested, the results here presented refer to a set of 30 image pairs from two onboard cameras. In the case of this data set, the target images are entirely overlapped by the source images. Images from the stereo camera where selected to be the source images, while images from a teleobjective camera where the target images. All image pairs where hand registered using Matlab. Figure 1 shows one of the image pairs from the data set (*bottom-left*) and a mosaic composed of the two images (*bottom-right*).

In order to compare the results of the proposed approach with the state of the art, seven of the nine algorithms used in a recent performance evaluation on color correction for image stitching applications [8] were used in the same data set. The other two algorithms were not used since [1] takes on average 140 seconds to correct a single pair of images and, regarding [3], it was not possible to find a public implementation to guarantee a fair comparison.

The evaluation parameters, i.e., *color similarity* (CS) and *structural similarity* (SS) were taken from [8] (see reference for their meaning). For better comparison of the proposed methodologies, the average processing time taken to correct one image is also presented.

TABLE I

AVERAGE AND STANDARD DEVIATION OF CS AND SS SCORES FOR THE SET OF SELECTED IMAGES. IT ALSO SHOWS THE AVERAGE PROCESSING TIME PER IMAGE. THE METHODS ARE SORTED BY AVERAGE CS SCORE. NOTE THAT THE FASTEST ALGORITHM [7] GETS THE WORST CS SCORE. THE PROPOSED ALGORITHM OBTAINS THE HIGHEST AVERAGE CS SCORE, THE SECOND BEST ON AVERAGE SS SCORE AND IS THE FASTEST PROCESSING OF THE TOP THREE IN CS SCORES.

Name of the Approach	Reference	CS μ	CS σ	SS μ	SS σ	Time (sec)
Baseline (Non corrected Image)	none	15.46	4.68	1.00	0.00	—
Gain Compensation	Brown 2007 [7]	15.51	2.47	0.98	0.02	0.21
Global Color Transfer in RGB	Xiao 2006 [5]	17.42	5.72	0.68	0.13	0.34
Global Color Transfer	Reinhard 2001 [4]	17.56	6.23	0.70	0.13	0.22
Cumulative Histogram Mapping	Fecker 2008 [2]	20.98	5.14	0.73	0.23	0.53
Principal Components Analysis	Zhang 2004 [6]	22.53	4.71	0.77	0.23	0.40
Local Color Transfer	Tai 2005 [9]	23.28	3.92	0.75	0.20	4.48
Brightness Transfer Function	Kim 2008 [10]	24.15	4.94	0.75	0.20	5.09
3D Gaussian Mixture Models	this paper	**24.30**	**4.06**	**0.77**	**0.21**	**4.10**

TABLE II

THE OUTPUT OF THE COMPARATIVE METHODS AND THE PROPOSED APPROACH (**GMM**) FOR THREE OF THE IMAGES IN THE DATA SET. THE IMAGE PAIRS ARE SHOW ON THE TOP OF THE TABLE. BELLOW EACH IMAGE THE ALGORITHM REFERENCE, CS AND SS SCORES ARE DISPLAYED. IN THE FIRST TWO IMAGES THE PROPOSED APPROACH OBTAINS THE BEST CS SCORE, WHILE IN THE THIRD IMAGE IT SCORES CLOSE TO THE BEST.

Table I shows the average CS and SS scores of the seven methods used for comparison, as well as of the approach proposed in the current paper. Analyzing Table I, two different classes of methods may be identified: fast methods [7], [5], [4], [2], [6], which have processing times under one second but have limited CS scores; and highly effective methods [9], [10] (and the proposed approach), which require about 10 times more time to get the highest CS scores. Note that this CS score corresponds to a logarithmic scale (see details in [8]). Results show that the proposed approach has the highest average CS scores and is the second best in average SS score. Also, considering the second class of tested methods, the proposed approach is the fastest one. The values presented in Table I are consistent with the evaluation performed by [8], where the best average CS scores were also from [9], [10].

Table II gives some qualitative results. Here it is also possible to verify that the proposed approach shows the greatest similarity with the reference source image.

IV. Conclusions

This paper proposes to use a single step multi dimensional probabilistic segmentation of the three color channels of an image in order to perform color correction. A recent performance evaluation on color correction, for a different context, was used to adequately select other color correction methods and an evaluation metric.

The joint segmentation of the three channel color reduces processing time from similar single channel methods: 4.1 average processing time of the proposed approach versus 4.48 from [9]. The proposed approach obtained the highest average CS scores, which makes it a technique to take into account for devising color correction algorithms. Of course real time color correction would not be possible, but if obtaining the highest CS is important, a strategy where a color palette mapping is built every four seconds could be devised. Results show that 3DGMM may be successfully applied to color correction in the context of multi-camera onboard systems, since it shows good results in the evaluation parameters and is faster to process than similar methods.

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