Correcting Chromatic Aberrations Using Image Warping

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Abstract

Chromatic aberration is due to refraction affecting each color channel differently. This paper addresses the use of image warping to reduce the impact of these aberrations in vision applications. The warp is determined using edge displacements which are fit with cubic splines. A new image reconstruction algorithm is used for nonlinear resampling. The main contribution of this work is to analyze the quality of the warping approach by comparing it with active lens control. Two different imaging systems are tested.

1 Introduction

In an imaging system, refraction causes each color channel to focus differently. This phenomenon is called chromatic aberration. Chromatic aberration (hereafter CA) is generally broken up into two categories: axial chromatic aberrations (ACA) and lateral chromatic aberrations (LCA), e.g. see [7]. ACA manifests itself as blurring; LCA as geometric distortions. Often these sources of degradation cause measurable differences in color images, e.g., a simple CCTV lens may have an LCA causing ≈ 1 pixel shifts between blue and red images. While this may seem to be a minor geometric disturbance, its effect on the measured RGB triples can be very large.

There are, at least, three things to do to combat CA. First, the traditional (and probably most effective) approach is to *buy good optics.** For a review of CA and related issues in lens design see [7], [5]. For a price, a lens can be designed to meet the most demanding imaging criterion. However, most vision researchers use inexpensive off-the-shelf lenses with, at best, simple CA correction. In addition, the correction of aberrations generally becomes more difficult/expensive as one reduces the focal ratio, increases the field of view, or allows zooming.

A more recent development is the use of active lens control to reduce CA. This technique, developed by R. Willson and S. Shafer at CMU [8]-[9], takes three separate images with slightly different focus and zoom settings designed to compensate for the optics. The active optics approach (hereafter AOA) has three main steps: 1) determination of best focus for each color channel, 2) determination of a magnification factor for red and green, 3) and determination of camera shift to align images. The first step uses adaptive focus, as in [4], thereby correcting for most of the ACA. The second step determines a magnification factor for each channel and uses this to actively control the zoom lens. The final step, to correct for differences in the optic axes, is done by physically shifting the camera. Unlike the focusing of step 1, steps 2 and 3 require some type of geometric calibration image. In [9], subpixel detection of vertical and horizontal edges is used to determine the zoom and displacements required. Note that the AOA allows one to reduce CA, even for chromatically corrected lenses. The major difficulties are that the RGB color channels must each be imaged separately (limiting it use with moving scenes), and the cost of the active system which requires digitally controlled focus and zoom, as well as precision positioners (shifts are $\approx$ .005in).

A third choice is to reduce the CA effects using image warping. We are not the first researchers to suggest using image warping for image registration or correction. For instance, NASA has used image warping in various applications [3], and much of the early work on image reconstruction centered around "digital correction" [6]. Often, remote sensing work "corrects" each spectral channel separately, thus providing some amount of LCA correction. We are unaware, however, of any quantitative study of the effectiveness of warping to correct for chromatic aberration.

2 Correction via Image Warping

There are two main parts to correcting CA using image warping: determining what warp to apply, and the actual implementation of that warp [2]. To facilitate comparison, we use the data from the work in [9], including original images, AO corrected images, and the location of horizontal and vertical edges in each of the R, G, and B images (with the blue image focused).

First, the geometric distortions must be computed. Using the edges (from [9]) in the blue image as the desired location, we compute displacements for the edges in the red and green images and then fit a cubic spline

*Unfortunately, [9] reports having found significant CA in many lenses, including SLR camera lens and ENG/EFP video lenses that were supposed to be corrected for CA.

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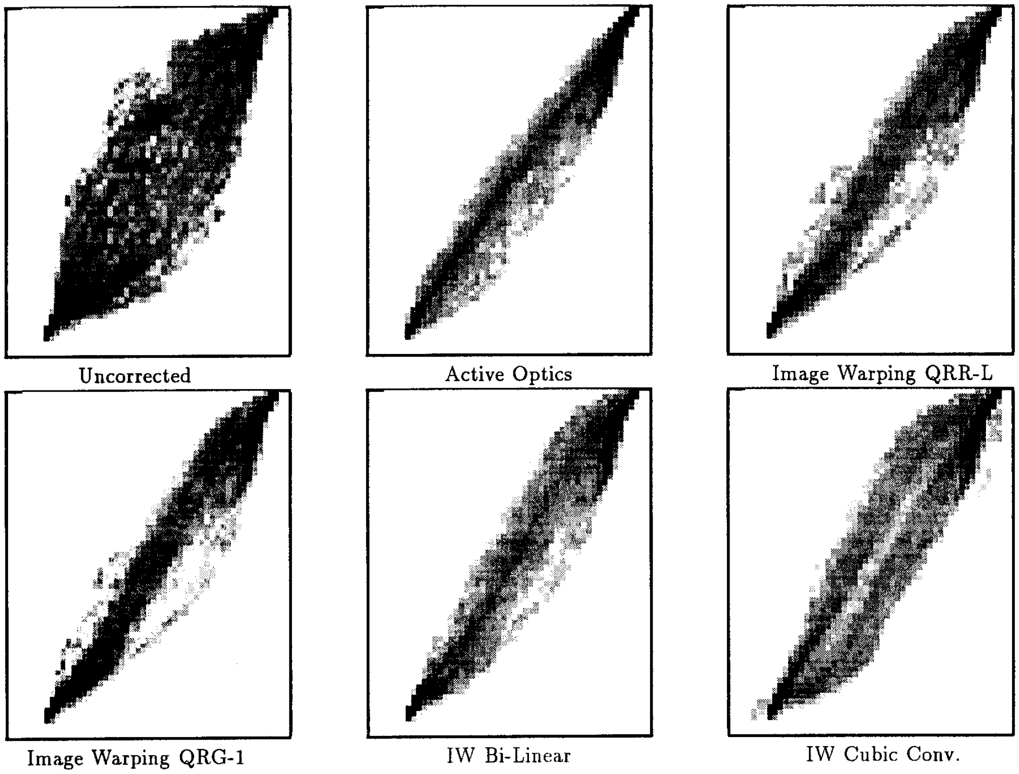

Figure 1: 2D histograms showing blue (vertical) versus red (horizontal) dispersion in color space for test case 1. The top row shows (left to right), the uncorrected images, the results of active optics, and the results of image warping with QRR L. The bottom shows image warping results using QRG CC-1, bi-linear and cubic-convolution with A=-1, respectively. Overall the active optics approach is better (tighter cluster) and also more symmetric in its error. The sigmoid shape which is slightly visible is caused by a different amount of blurring in each color channel. Note black = 1000, and some bins are clipped.

through these displacements (separately for x and y). The warp is then the tensor product of these splines. Other features could be used, e.g., [3] used correlation between features in each color channel, as well as *a priori* calibration information.

Image warping is commonly used in graphics, where subjective qualitative assessment is sufficient. To use image warping in vision we need more quantitative assessments. For complex warps we previously described a technique to increase the accuracy of the warp while maintaining low cost, see [10]. Fortunately, the warps for CA correction are not severe and a simple 2-pass separable technique can be used, reducing warping to a problem in 1D reconstruction and non-linear resampling. We use imaging-consistent reconstruction filters [1], which employ a model of PSF (blur) *within a pixel* to define a functional restoration. This functional form is then warped, and reblurred according to an output PSF, using an approach called the integrating resampler [11]. The following acronyms are used to refer to reconstruction techniques defined in [1]: QRR L for quadratic restoration with a box (rect) PSF and linear approximation for edge points, and QRG CC-1 of quadratic restoration with Gaussian-like PSF and cubic-convolution with parameter -1 for the approximation of edge points. Previous researchers considered other techniques, e.g. [3], used bi-linear interpolation with point sampling, [6] considers pure cubic convolution.

3 Experimental comparison

Some of the data that CMU used to evaluate their AOA (see [9] for more details) is used here to allow direct comparison. Test case 1 used a General Imaging camera with a Cosmicar motorized zoom lens (12.5-75mm). Test case 2 used a Photometrics camera with a Fujinon motorized zoom lens. A 1/2" BW checkerboard was imaged at a distance of $\approx 1.5m$. Separate R,G and B images were taken using Wratten filters. In [9] quality was measured using edge displacement. Since we

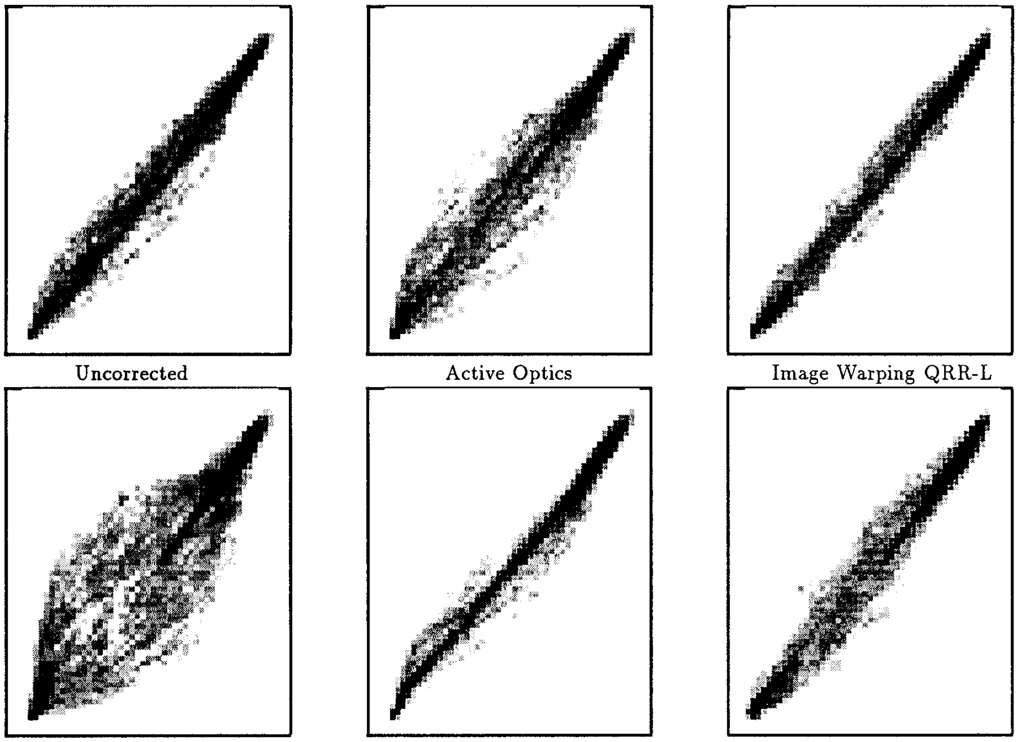

Figure 2: 2D histograms showing dispersion in color space for test case 2. The top row shows results on the red channel (left to right), the uncorrected red channel, the results of active optics, and the results of image warping with QRR L. The bottom row shows the green channel (left to right), uncorrected, the results of active optics, and the results of image warping with QRR L. For this "chromatically corrected" lens we plot black=100. We note that the chromatic spread is still significant. The maximum error in the red channel actually gets worse with the AO approach.

directly manipulate geometry, we felt color-based error measures should be used.

Obviously, all pixels should lie on a line in RGB space. To visualize the errors we use two techniques: direct display, and quantitative error measures. Direct display uses 2D histograms, see figures 1- 2, where the (x,y) location of a bin is determined by the (r,b) (or (g,b)) pixel values. The plots shown have 64x48 bins with intensity encoding the log of the number of points per bin, with some bins clipped. The important information in these plots is the spread of the points around their "central" linear tendency, the wider the spread, the greater the CA.

The first quantitative measure, *Gray-line error*, is the mean squared distance between the RGB triples and the line defined by least squares fitting with distance measured normal to the line. This error measure relates to the color shift of a pixel. The remaining measures are more sensitive to blur within the image. Using a local calibration technique, [2], we determine local black and white reference values (BW values) used to define three error measures. Define *BW-RGB error* as the mean pointwise distance from each RGB triple to the nearer of the BW values. Finally, define *BW-R error* (*BW-G error*) as the mean distance between the r (g) value of a pixel and the closer of the BW-value's red (green) components. Obviously, smaller error measures are better, but because of lighting variations, camera noise, blurring and errors in calibration, zero measures should not be expected.

The histograms and error measures are presented in in figures 1–2 and table 1. See the figure/table captions for more discussion. (Note the tables in [2] are incorrect).

4 Conclusions and future work

This paper demonstrates the use of image warping for the correction of chromatic aberration. The technique was applied to images from two different cameras /

Algorithm	Test case	Window	Gray-line error	BW-RGB error	BW-R error	BW-G error
Uncorrected	CCTV	[15 465][15 497]	1.96	19.16	12.33	9.54
Active Optics	CCTV	[15 465] [15 497]	1.80	17.37	10.56	9.18
Image Warping QRR L	CCTV	[15 465] [15 497]	1.33	18.87	12.38	9.55
IW QRG CC-1	CCTV	[15 465] [15 497]	1.37	18.89	12.38	9.58
IW Bi-linear Interp.	CCTV	[15 465] [15 497]	2.80	19.12	12.57	9.70
IW Cubic Conv. A=0	CCTV	[15 465] [15 497]	7.47	18.98	12.31	9.46
IW Cubic Conv. A=-1	CCTV	[15 465] [15 497]	6.36	19.64	12.85	10.00
Uncorrected	Fujinon	[15 322] [15 322]	5.77	14.41	7.96	7.50
Active Optics	Fujinon	[15 322] [15 322]	4.12	14.30	7.92	7.70
IW (QRR L)	Fujinon	[15 322] [15 322]	4.66	14.66	8.05	8.17

Table 1: Table of quantitative error measures. Depending on the measure of quality emphasized and the lens tested, either the Image Warping or the Active Optics will appear better. For the Fujinon lens, AO was better in all quantitative categories even though its maximum error in the red channel is greater (see figure 2). For the CCTV lens, when blur is considered, AO is the better choice. When RMS error to the *Gray-line* is considered image warping was superior. Bi-linear interpolation performs measurably worse in all cases. Finally, cubic convolution seems worse than the uncorrected image, although the qualitative results looked better. We are still investigating this behavior of CC. We note that the least-squares line fitting can be hard to predict from the qualitative histogram because of clipping in the histogram bins, and because it is fitting in RGB space, not the 2D space of the plots.

lenses. In general, the active optics approach [9], is superior to image warping because it can correct for blur defects. However, in the CCTV test case, the new image warping techniques reduced the mean squared error to the gray line more than the active optics approach. For the test other case, image warping had a larger MS error, but did have a noticeably larger reduction in the maximum error. Image warping would be even better with the images focused on yellow rather than blue. The proposed warping methods used new image reconstruction/restoration methods [1]. Image warping with either linear or cubic convolution filters had considerably larger errors. Future work will address building a calibration model for image warping for different zoom/focus settings.

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