

CV PROJECT REPORT

Color Homography Color Correction

Team Name: SSK

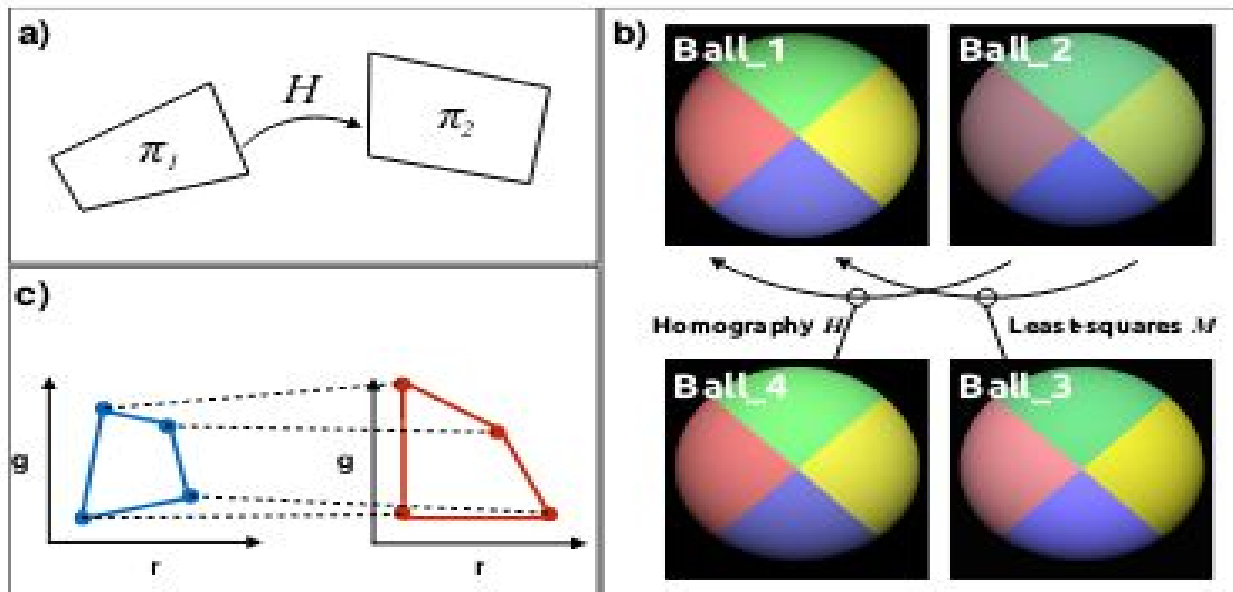
Team ID:17

Aim

- To show the surprising result that colors across a change in viewing condition (changing light color, shading and camera) are related by a homography.
- To evaluate Color Homography Color Correction methods like Alternating Least Squares Method, RANSAC Method, Least Square Method.

Motivation

- In geometry computer vision, an homography relates two planes.
- In color, an homography relates two photometric views.
- In this method, they proposed that to map one photometric view to another we must map the colors correctly independent of shading.
- Since shading only affects the brightness, or magnitude, of the RGB vectors, it is possible to find the 3×3 map which maps the color rays (the RGBs with arbitrary scalings) in one photometric view to corresponding rays in another.



Explanation of the above figure:

- We aspire to transfer color of Ball_1 to Ball_2. (Fig. b)
- Fig. c shows chromaticity diagrams of Ball_1 and Ball_2 being related by a Homography.
- Fig. a shows image planes being related by a chromaticity diagram.

Overview

- Introduction to Color Homography.
- Implementation of three algorithms for calculating Color Homography Color Correction. They are:
 - Least Square Color Correction
 - Alternating Least Squares Color Correction
 - RANSAC Color Correction
- Evaluation of the above Color Correction Algorithms using the following color spaces:
 - CIE L*a*b color space
 - CIE L*u*v color space
 - RGB color space
- Conclusion based on the above results as to which method is Algorithm gives more robust results.

Color Homography Theorem

Statement

- Chromaticities across a change in capture condition (light color, shading and imaging device) are a homography apart.

Proof

- First we assume that across a change in illumination or a change in device where the shading is the same the corresponding RGB's are related by a linear transform M
- Clearly, $H = CM C^{-1}$ maps colors in RGI form between illuminants.
- Due to different shading, the RGI triple under a second light is represented as $c' = \alpha' c H$, where α' denotes the unknown scaling.
- Without loss of generality let us interpret c as a homogeneous coordinate i.e. assume its third component is 1.
- Then, $[r' g'] = H ([r g])$ (chromaticity coordinates are a homography $H()$ apart).

Color Homography Color Correction Algorithms

1. Least square Color Correction

A is the input image matrix

B is the reference image matrix

A and B are reshaped to have the dimensions: [3, No. Of pixels in the image]

$AM=B$

We find M by using least squares method

2. Alternating Least Squares Color Correction

- Terminology
 - H- Homography Matrix (Captures Color Correction Component)
 - D- Shading Matrix (Captures Shading Correction Component)

Pseudo Code

- N - Number of pixels in the image
- A - nx3 matrix of RGB's
- B - nx3 matrix of corresponding XYZ's.
- D - nxn diagonal matrix of shading factors
- H - 3x3 color correction matrix
- Finally B can be computed as follows
 - **With shading correction** : from the equation $DAH \approx B$
 - **Without shading correction** : $DA \approx B$

```
1  $i = 0, \min_{D^0} \|D^0 A - B\|_F, A^0 = D^0 A;$ 
2 repeat
3    $i = i + 1;$ 
4    $\min_{H^i} \|A^{i-1} H^i - B\|_F;$ 
5    $\min_{D^i} \|D^i A^{i-1} H^i - B\|_F;$ 
6    $A^i = D^i A^{i-1} H^i;$ 
7 until  $\|A^i - A^{i-1}\|_F < \epsilon;$ 
```

Results for ALS and LS Color Correction Algorithms

Image-1

- A- input image
- B- reference image
- The other three images are
 - (1) A to B with shading correction
 - (2) A to B without shading correction
 - (3) A to B by least squares

Image-2

- (1) Chromaticity diagram before applying homography. Purple -image B green-image A.
- (2) Chromaticity diagram after applying just homography
- (3) Chromaticity diagram after applying both homography and shading correction

A



B



A to B with shading correction



A to B without shading correction



A to B by Least-Squares



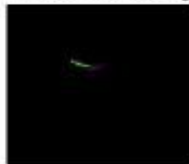
original chromaticity diag of both images



after using H chromaticity diag of both images



after using both H,D chromaticity diag of both images



A



B



A to B with shading correction



A to B without shading correction



A to B by Least-Squares



original chromaticity diag of both images

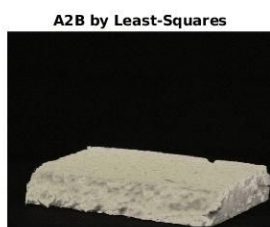
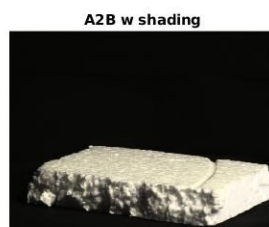
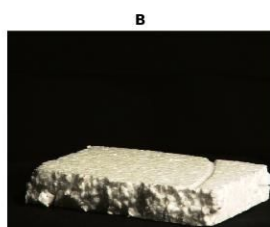
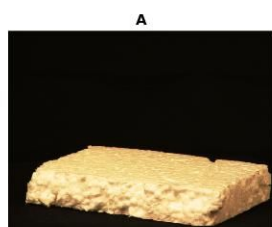


after using H chromaticity diag of both images



after using both H,D chromaticity diag of both images





original chromaticity diag of both images



after using H chromaticity diag of both images



after using both H,D chromaticity diag of both images



A



B



A2B w shading



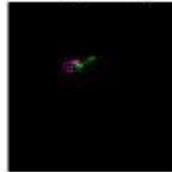
A2B w/o shading



A2B by Least-Squares



original chromaticity diag of both images

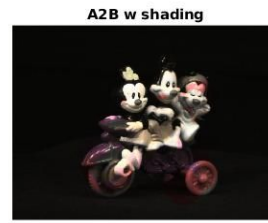


after using H chromaticity diag of both images



after using both H,D chromaticity diag of both images

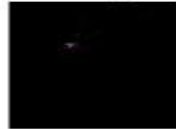




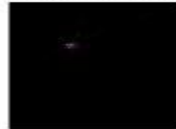
original chromaticity diag of both images



after using H chromaticity diag of both images

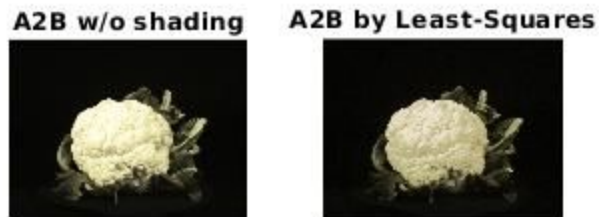


after using both H,D chromaticity diag of both images

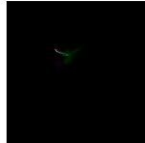


Note:

- If we observe the mickey mouse images in Input A and Input B, we observe that mickey mouse in A is facing to the observers left and in B it is facing to the observers right.
- When we use color transformation using ALS Homography with shading correction, we can see structural differences in the Input Image A and reconstructed image along with color difference.
- This structural difference occurs because D (Shading Matrix), takes into account these structural differences as shading variation and not difference in images.
- In the reconstructed image using just ALS Homography matrix, mickey mouse is facing towards left as in Input A which is expected.
- But in the reconstructed image using ALS Homography matrix and Shading matrix, mickey mouse is facing towards right as in Input B which is not expected, because D matrix considers this structural change as shading.



original chromaticity diag of both images



after using H chromaticity diag of both images



after using both H,D chromaticity diag of both images



Note:

- If we observe the cauliflower image Input A and Input B, both images are not exactly identical.
- When we use color transformation using ALS Homography with shading correction, we can see structural differences in the Input Image A and reconstructed image along with color difference.
- This structural difference occurs because D (Shading Matrix), takes into account these structural differences as shading variation and not difference in images.

A



B



A2B w shading



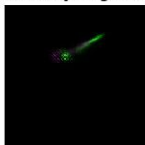
A2B w/o shading



A2B by Least-Squares



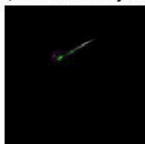
original chromaticity diag of both images



after using H chromaticity diag of both images



after using both H,D chromaticity diag of both images



A



B



A2B w shading



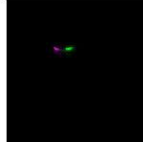
A2B w/o shading



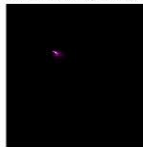
A2B by Least-Squares



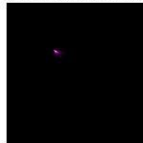
original chromaticity diag of both images



after using H chromaticity diag of both images



after using both H,D chromaticity diag of both images



A



B



A2B w shading



A2B w/o shading



A2B by Least-Squares



original chromaticity diag of both images



after using H chromaticity diag of both images



after using both H,D chromaticity diag of both images



A



B



A2B w shading



A2B w/o shading



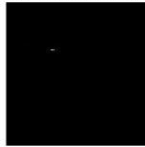
A2B by Least-Squares



original chromaticity diag of both images



after using H chromaticity diag of both images



after using both H,D chromaticity diag of both images



3. RANSAC Color Correction

Chromaticity Diagrams:

- They can be defined to have a size $N_{bin} \times N_{bin}$
- Steps to compute Chromaticity Diagram of an image A:
 - a. Resize A to have dimensions $[3, \text{Number of pixels}]$. Let this matrix be A'
 - b. Convert RGB space to RGI space by multiplying A' with C. Let $B = CA'$
 - c. $C = [1 \ 0 \ 1; 0 \ 1 \ 1; 0 \ 0 \ 1]$
 - d. Homogenise B by dividing R, G with I space.
 - e. Construct a 1-d histograms for R and G space independently such that bin size of this histogram is $1/N_{bin}$. Let these histograms be histR and histG.
 - f. Now construct a 2-D matrix Chrodist of dimensions $N_{bin} \times N_{bin}$ such that $Chrodist[i,j] = \text{Number of pixels falling in the } i\text{th bin of histR and } j\text{th bin of histG}$.

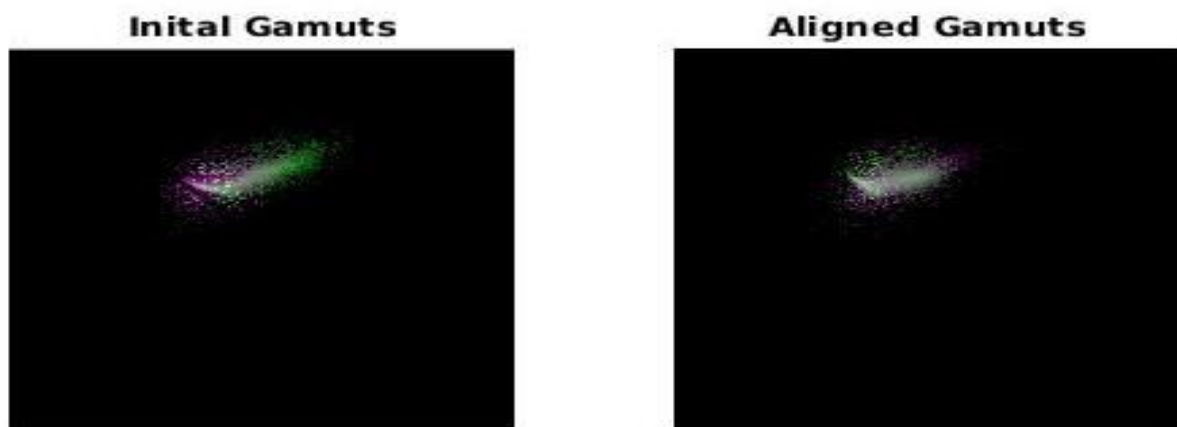
Pseudo Code:

1. Input Image A to which color of Input Image B has to be transferred to form Image C
2. Construct Chromaticity diagrams of Image A and Image B as explained above.
3. Detect ASIFT features in chromaticity diagrams of Image A and B and find best matches. Smoothen Chromaticity diagrams of A and B to get required number of matches.
4. H matrix contains 9 variables (8 independent). Each match point gives 2 equations. Hence 4 match points are sufficient to find the Homography matrix.
5. We randomly choose 4 points out of the matched feature set.
6. We require at-least 3 points out of the 4 randomly chosen points to be non collinear to get a valid Homography matrix. This will ensure that all the 4 points are non-collinear. We check for this degeneracy of the set of 4 points using all possible combinations of 3 points from this set.
7. If we get a valid set we compute H using ALS algorithm.
8. We repeat steps 5-7 until convergence criteria is satisfied.
9. Convergence criteria is defined in the below two ways:
 - a. If number of trials of RANSAC are greater than 5000 (OR)
 - b. We define $N = \log(1-p)/\log(pNoOutliers)$, where $p=0.99$ and $pNoOutliers = \#(outliers) / \#(Total \ Points)$. We converge if $N > \#(trials \ so \ far)$

Note

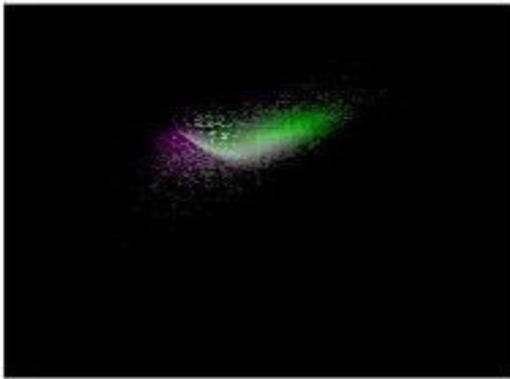
- Computing Shading matrix (D) using RANSAC Color Correction with ALS as the fitting function will result in a D matrix of dimensions 4×4 .
- In order to generate a shading correction matrix for the whole image, we require the dimensions of D to be $N_{pixels} \times N_{pixels}$.
- Hence, shading correction cannot be done using RANSAC Algorithm.

- Results for Ransac:



Matches in Chromaticity diagram using ASIFT

Initial Gamuts



Aligned Gamuts



original



reference



estimated



Matches in Chromaticity diagram using ASIFT

original



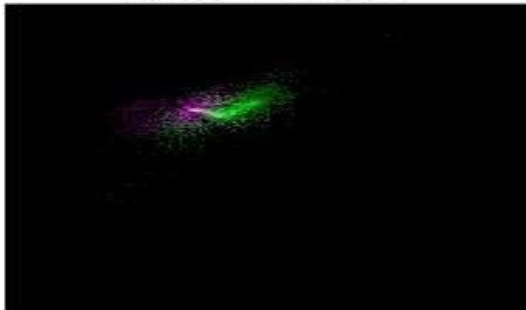
reference



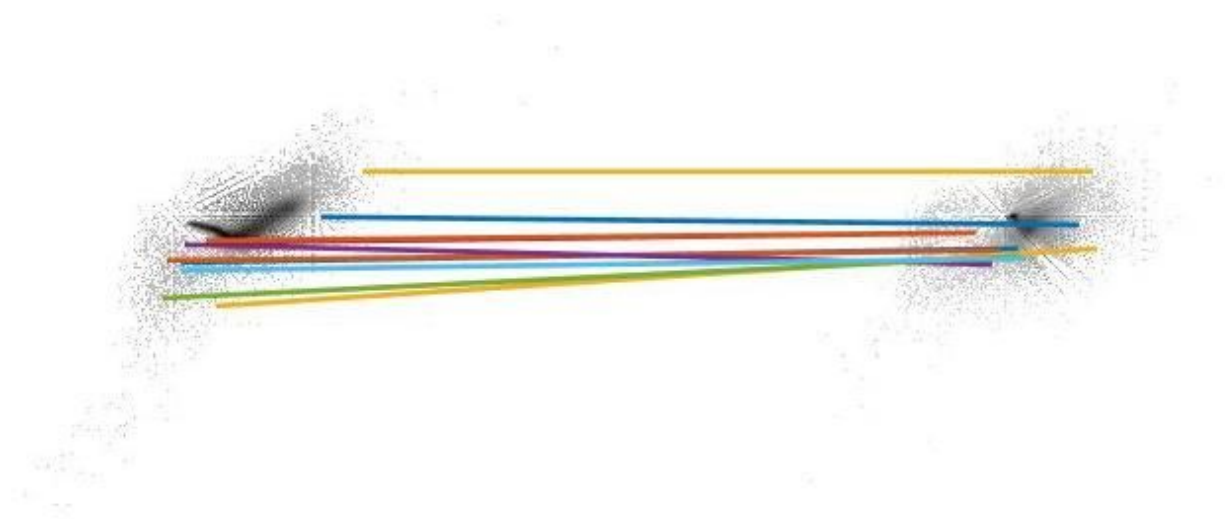
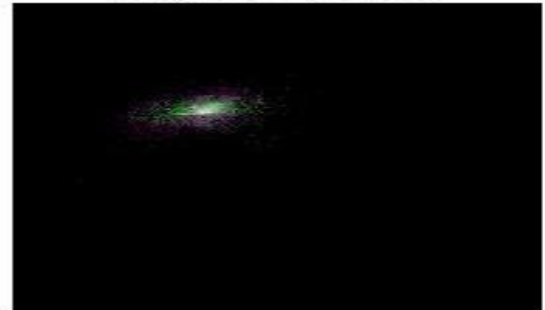
estimated



Initial Gamuts



Aligned Gamuts



Matches in chromaticity diagrams using Asift

original



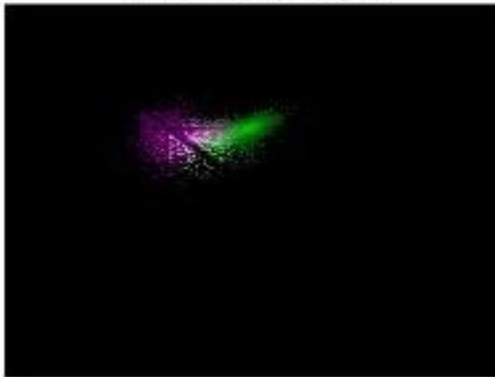
reference



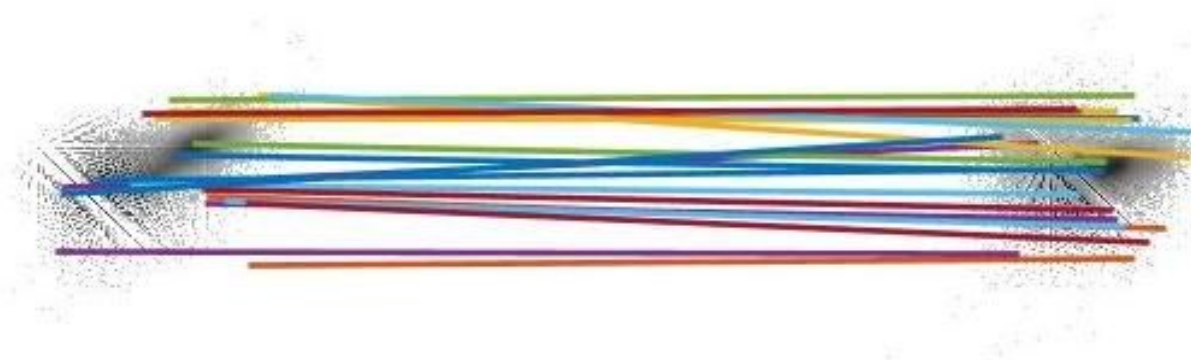
estimated



Initial Gamuts



Aligned Gamuts



Matches in Chromaticity diagram using ASIFT

original



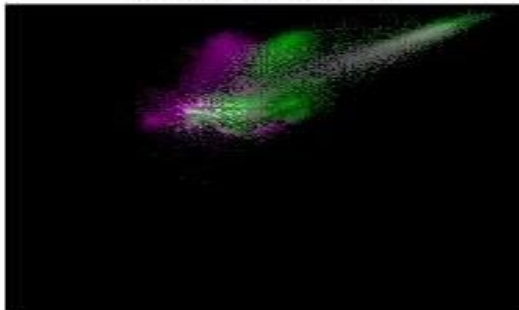
reference



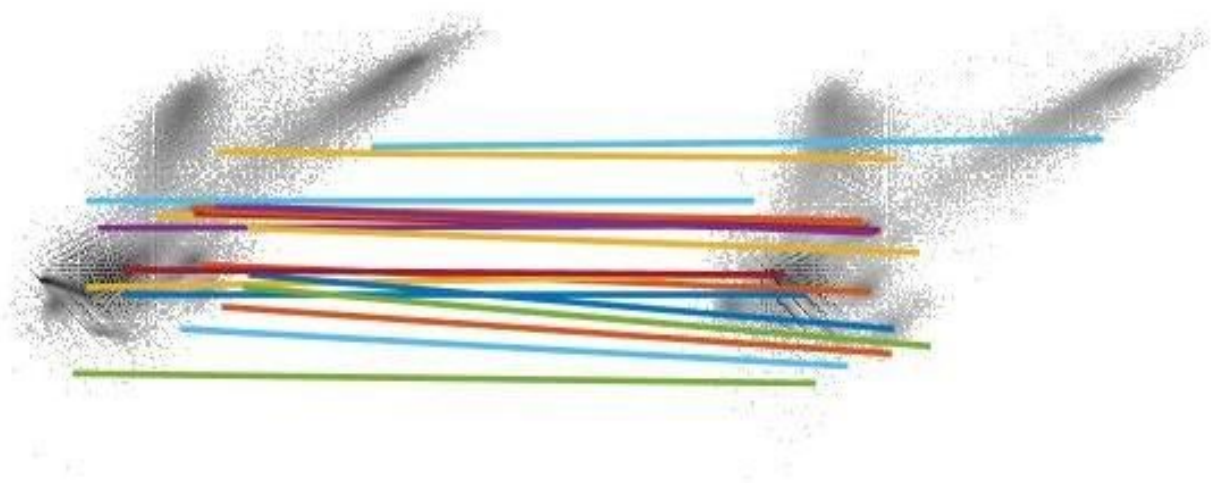
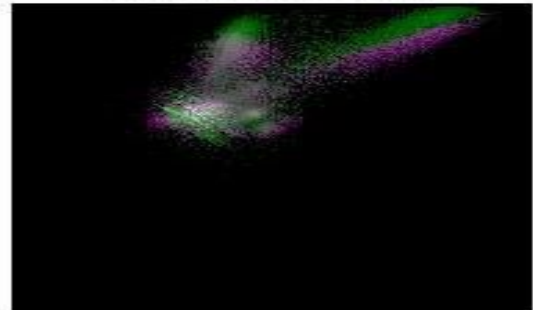
estimated



Initial Gamuts



Aligned Gamuts

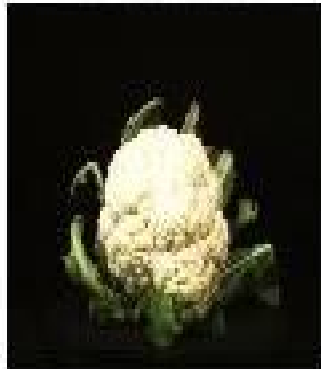


Matches in Chromaticity diagram using ASIFT

original



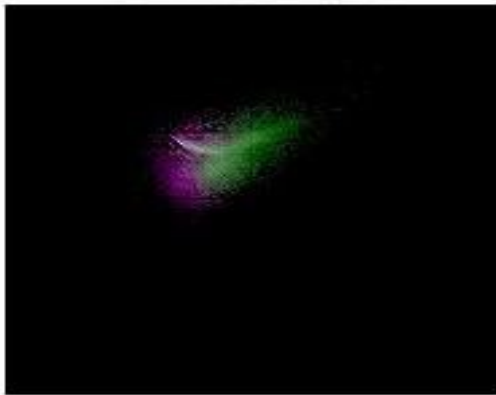
reference



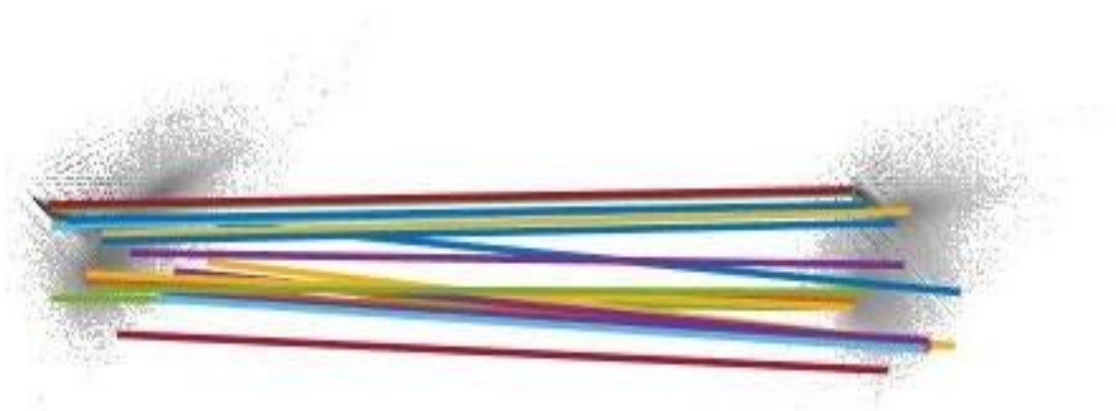
estimated



Initial Gamuts



Aligned Gamuts



Matches in Chromaticity diagram using ASIFT

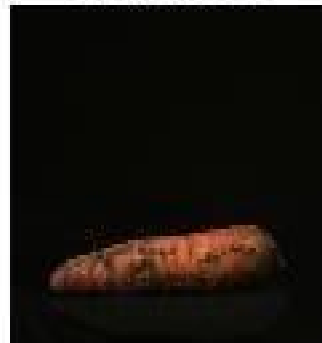
original



reference



estimated



Initial Gamuts



Aligned Gamuts



Matches in Chromaticity diagram using ASIFT

original



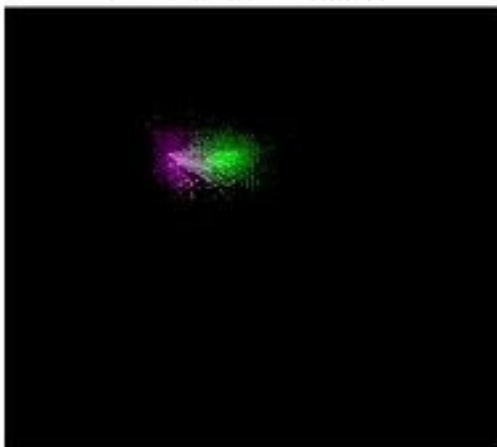
reference



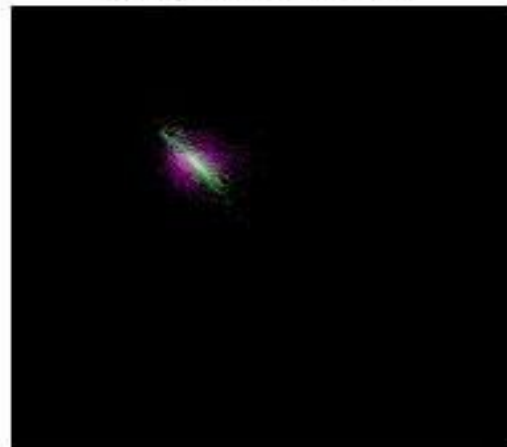
estimated



Initial Gamuts



Aligned Gamuts



Matches in Chromaticity diagram using ASIFT

Comparing the results of Ransac and ALS:

- In Ransac the shading correction is not captured and the original structure of the input image is not affected whereas in ALS colour correction the shading is captured but the original structure of the input image is disturbed.

Evaluation Methods

- We wish to evaluate color correction when shading varies across the color target (in this case a Macbeth Color Checker).
- First we measure, in the lab, the actual ground truth XYZs. We call them `ref_colors`.
- Second we, in situ, measure the RGBs in a raw image where the shading can vary across the chart.
- We now solve directly for the correction matrix mapping the RGBs to XYZs.
- We apply the three computed correction matrices (least-squares, ALS, RANSAC and Root Polynomial) to the RGBs from the checker where the effects of intensity variation has been removed. This color is called `sv_uniform`.
- The intensity variation is removed by dividing by the brightness image of a uniform grey checker images in the same location in the same scene.
- The colors obtained without dividing by grey values are called `sv_nonuniform`.
- In evaluating our algorithms we will use RGB, CIE $L^*a^*b^*$ and CIE $L^*u^*v^*$.
- We use a dataset of 13 images in which are 9 images are captured indoor and are 4 captured outdoor.
- The dataset also provides us with standard color values for both indoor and outdoor.
- We compute two kinds of homography matrices `H_uniform` and `H_nonuniform` by mapping `ref_colors` with `sv_uniform` and `sv_nonuniform` respectively, using least-squares, ALS and RANSAC algorithms.
- We use `H_uniform` and `H_nonuniform` on `sv_uniform` to get reconstructed `reconstructed_ref_uniform` and `reconstructed_ref_nonuniform`.
- The error between `reconstructed_ref_uniform` and `ref_uniform` in RGB, CIE $L^*a^*b^*$ and CIE $L^*u^*v^*$ color spaces gives uniform error in RGB, CIE $L^*a^*b^*$ and CIE $L^*u^*v^*$ spaces.
- The error between `reconstructed_ref_nonuniform` and `ref_nonuniform` in RGB, CIE $L^*a^*b^*$ and CIE $L^*u^*v^*$ color spaces gives non uniform error in RGB, CIE $L^*a^*b^*$ and CIE $L^*u^*v^*$ spaces.
- We even compared our results with another method called Root polynomial which is not mentioned in the paper .
- The RGB's are mapped to a standard colour space such as XYZ - useful for colour measurement- by a mapping function e.g. the simple 3×3 linear transform. This mapping, which we will refer to as LCC (linear colour correction), has been demonstrated above. An alternative and potentially more powerful method for colour correction is root polynomial colour correction (RPCC). Here, the R, G and B values at a pixel are extended by the polynomial terms.

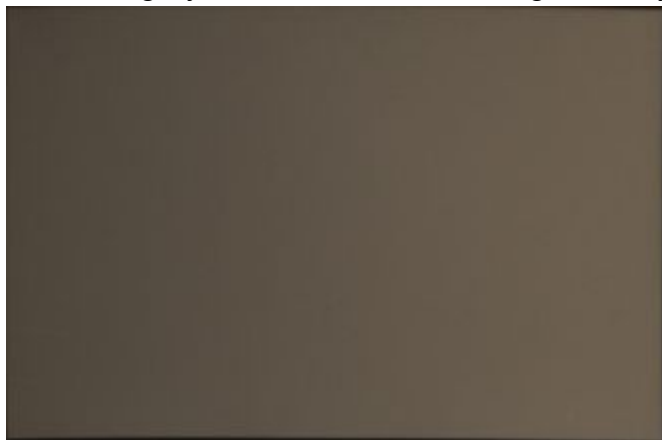
Macbeth Color checker Outdoor Images:



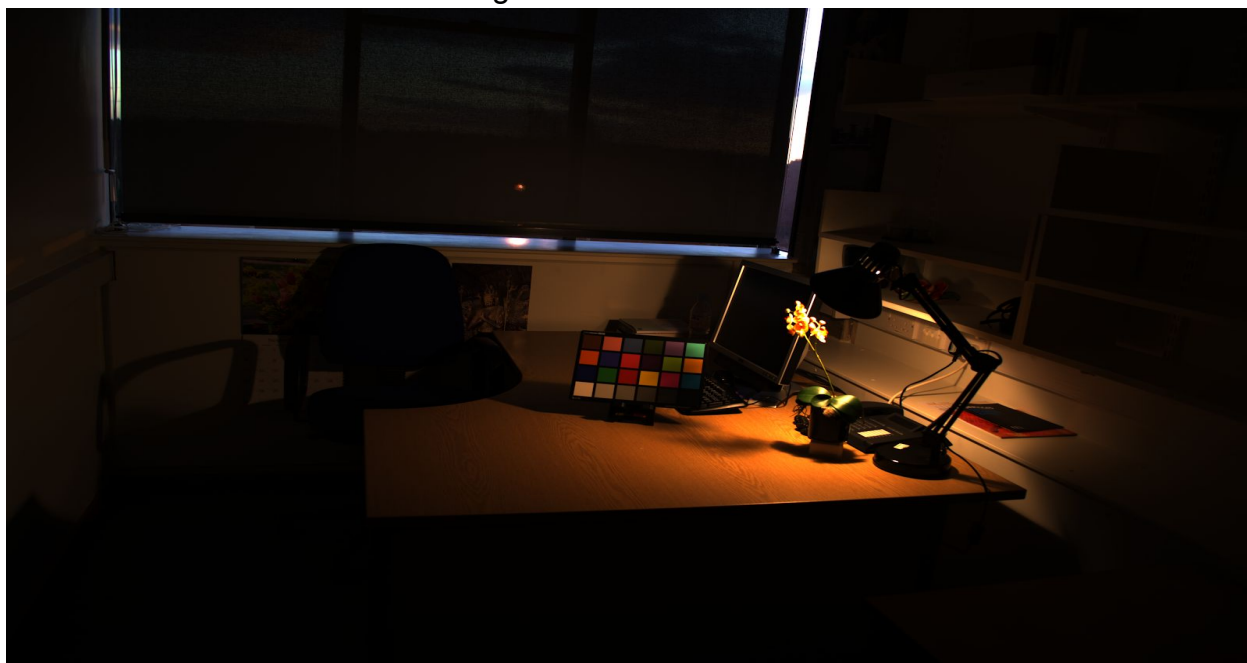
Just the Macbeth Color Checker Cropped



A uniform grey chart used for removing intensity variation



Macbeth Color checker Indoor Images:



Just the Macbeth Color Checker Cropped



A uniform grey chart used for removing intensity variation



- The actual ground truth XYZ's for the Cloudy images: (24*3)

```

55.2932  51.5013  34.1946
168.8049 137.5587  32.2029
38.8573  33.2114 120.1809
380.2029 414.2129 398.1538
163.8523 155.1836 107.3277
65.8361  60.5818 173.5709
71.9976 117.4143  49.2004
248.6073 270.6497 272.9264
80.8573  89.6038 147.8040
129.1495  90.3575  63.4345
93.2629  60.4423  26.5652
155.9322 170.0556 172.7791
50.4446  64.2079  32.5813
41.5167  33.2643  65.5489
251.9290 274.1970  46.3682
85.0164  92.0874  93.1669
113.6929 111.4793 187.9539
154.8324 206.2811  54.5640
136.9638  92.3213 138.4716
40.5331  44.1930  45.8763
138.5231 195.8882 189.3401
204.2379 196.6661  38.4270
69.9051  97.9929 170.3417
17.3816  18.8311  19.8661

```

- The actual ground truth XYZ's for the in images:(24*3)

```

56.5609 52.7016 35.8013
169.1144 138.3697 34.5155
40.3666 34.7302 122.7049
373.7998 406.0503 394.9597
163.9629 155.3200 109.6890
67.2632 61.9583 176.2856
72.8959 118.1088 51.5714
246.3554 267.3186 274.0968
81.9209 90.3640 150.4420
130.4345 91.7767 65.6318
95.3425 62.3332 28.5699
155.5547 169.0702 174.7915
51.3842 65.2261 34.2115
43.1066 34.8180 68.0494
250.3807 272.7233 48.6788
86.0638 92.9404 95.4401
114.6472 112.1249 190.3411
155.2531 206.3527 56.9795
137.9070 93.4378 141.0641
41.7531 45.3754 47.6346
138.4967 194.6521 191.3573
204.0535 197.0235 40.6066
70.9412 98.5281 172.3545
18.6981 20.1824 21.6442

```

We got these values directly from the dataset which we used to generate the above mean ,median,percentage 95 results.

Results obtained for Evaluation methods

RGB (Uniform)

	Mean	Median	pct95	Max
ALS	0.041623	0.027836	0.14813	0.24922
ALS_RANSAC	0.041547	0.026378	0.14929	0.25347
LS	0.061237	0.044642	0.17958	0.29625
RP	0.08557	0.057541	0.2789	0.33551

DeltaE LAB 1976 (Uniform)

	Mean	Median	pct95	Max
ALS	3.5484	2.8698	8.6401	9.5442
ALS_RANSAC	3.4298	2.6934	9.0717	10.194
LS	3.6672	3.178	8.2983	9.0491
RP	2.7682	2.0858	7.034	7.9857

DeltaE LUV (Uniform)

	Mean	Median	pct95	Max
ALS	4.0306	3.344	9.242	9.9202
ALS_RANSAC	3.8881	3.1339	9.6441	10.679
LS	4.0335	3.5371	8.9445	9.6683
RP	2.9904	2.5466	6.9428	8.8586

RGB (Non-Uniform)

	Mean	Median	pct95	Max
ALS	0.041623	0.027836	0.14813	0.24922
ALS_RANSAC	0.041547	0.026378	0.14929	0.25347
LS	0.061237	0.044642	0.17958	0.29625
RP	0.08557	0.057541	0.2789	0.33551

DeltaE LAB 1976 (Non-Uniform)

	Mean	Median	pct95	Max
ALS	3.548	2.8699	8.6391	9.5421
ALS_RANSAC	3.4174	2.6591	8.9944	10.32
LS	5.3935	4.7568	11.669	12.885
RP	6.6968	5.4794	20.437	25.8

DeltaE LUV (Non-Uniform)

	Mean	Median	pct95	Max
ALS	4.0295	3.3432	9.2387	9.9175
ALS_RANSAC	3.8805	3.0788	9.6856	10.794
LS	6.0887	5.7169	13.164	14.085
RP	7.005	6.3586	17.372	21.14

Analysis of the above obtained results

- The mean, median, 95% quantile and max ΔE errors are reported for RGB, CIE L*a*b* and CIE L*u*v* spaces using both uniform and non-uniform Homography matrices.
- It is clear that RANSAC- homography-based color correction supports a significantly improved color correction performance compared with the simple least square (all error measures are about 40% improved).
- Compared with the ALS color correction, all mean errors are improved by about 10%, and all median errors are improved by about 20%, at the cost of getting slightly higher 95% quantile error and maximum error.
- Hence, RANSAC-based color homography color correction is robust to outliers and delivers improved color fidelity.

Conclusion:

- The complete paper including the evaluation metrics has been implemented.
- We even compared our method with other methods such as root polynomial colour correction
- The results we obtained are almost similar to the results in the paper.

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