Object Recognition In Different Illumination Conditions

RISS: Krishna Kumar Singh Advisors: Edward Hsiao , Prof. Martial Hebert

THE ROBOTICS INSTITUTE

Carnegie Mellon University

OBJECTIVE

Objects exhibit different colors under different illumination conditions. We build models which capture these variations in colors for use in object recognition.

THE ALGORITHM

Alignment Of Macbeth Color Chart

- Captured 130 images of the Macbeth Color Chart in various illumination conditions.
- Used fast **corner detector** to find the corners of the Macbeth Color Charts
- Used **homography** to align those corners to standard rectangle of size 800 X 600.
- Finally, used **affine flow** to align all the 130 images together.

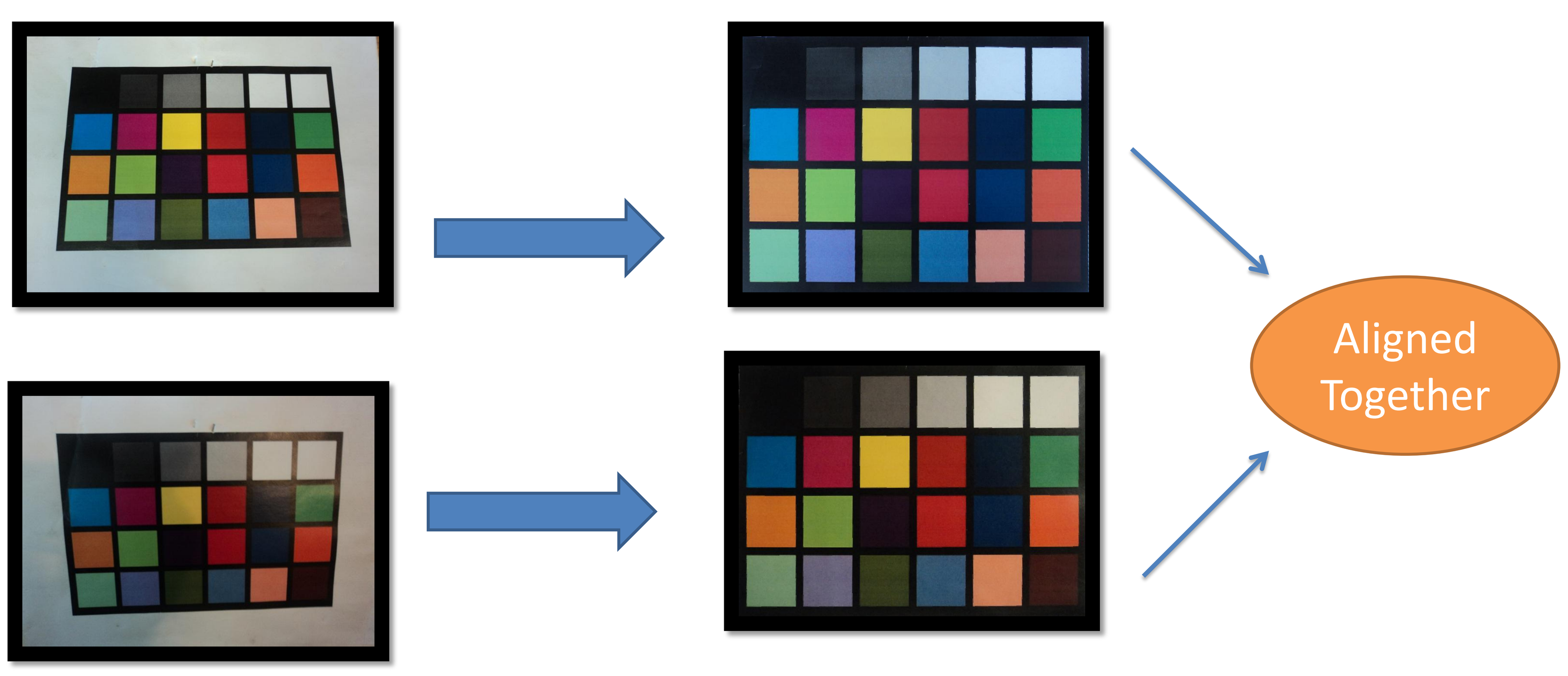


Figure showing results after alignment of the Macbeth Color Charts

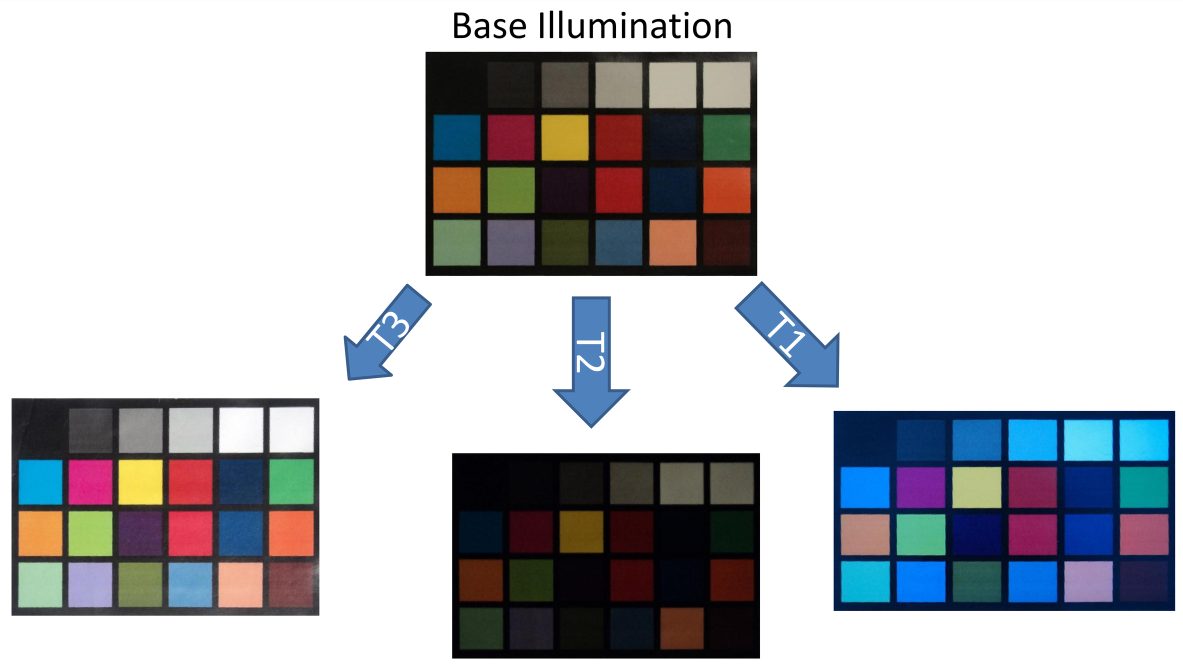
Finding Linear Color Transformations [1]

- Once the images are aligned , we find the linear color transformations corresponding to base illumination in the following color spaces :-

Color Space	2-D	3-D
• RGB	Normalized(R), Normalized(G)	R , G, B
• HSI	H , S	H , S , I
• YCbCr	Cb , Cr	Y , Cb , Cr

- We use **MSE** (Minimum Square Error) to find linear color transformations matrix corresponding to base illumination .
- In case of 2D & 3D we got 2 X 2 and 3 X 3 linear color transformation matrix respectively.

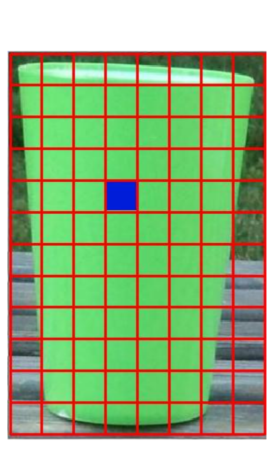
Base Illumination



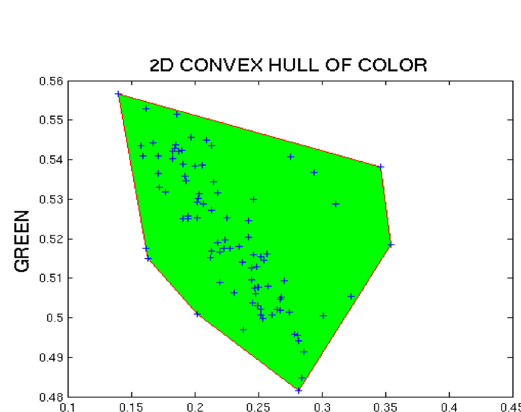
Here T1 , T2, T3 … Tn are various transformation matrix corresponding to base image. Error in transformation was more in HSI space as its linear color transformation is not possible, so we discarded it for the further process.

Creating Color Convex Hull

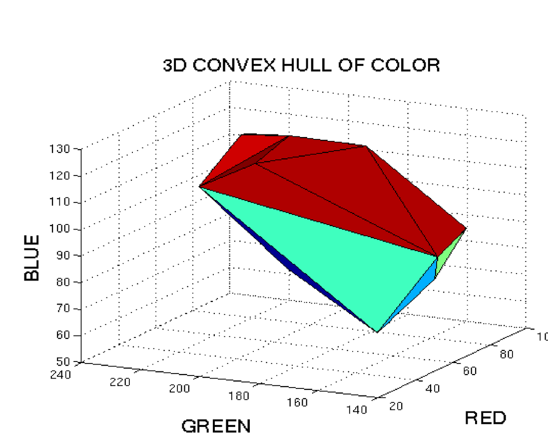
- For each model object image, we collect a Macbeth chart to determine the illumination of the object.
- Then we divide image into grid cells.
- For each cell we apply 2D and 3D transformations to obtain 2D and 3D **convex hull** respectively.



Object Divided Into Bins



2D convex hull corresponding to bin marked in blue



3D convex hull corresponding to bin marked in blue

Distance Of Point P from Convex Hull

$$\text{Distance(P)} = \begin{cases} 0 , \text{ if P inside convex hull} \\ \text{Shortest Euclidian distance from the edge and facets of 2D} \\ \text{and 3D convex hull respectively , if P is outside convex hull} \end{cases}$$

Detecting Objects And Pipelining it with Rline2D [2]

- Now the test image is also divide into grid cells. We then run template matching on it .
- We take average of the colors in a cell and represent it as a point. Then we compute the score as cumulative sum of distance of neighboring color points from the convex hulls .
- Use 3D convex hull if object has low saturation color otherwise use 2D convex hull
- Then we run **Mean Shift** on the score map, to find the detection points.

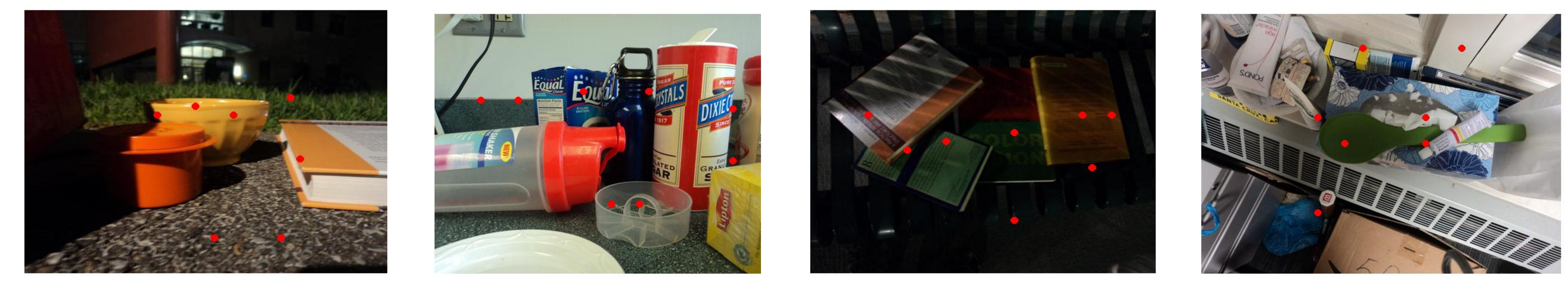
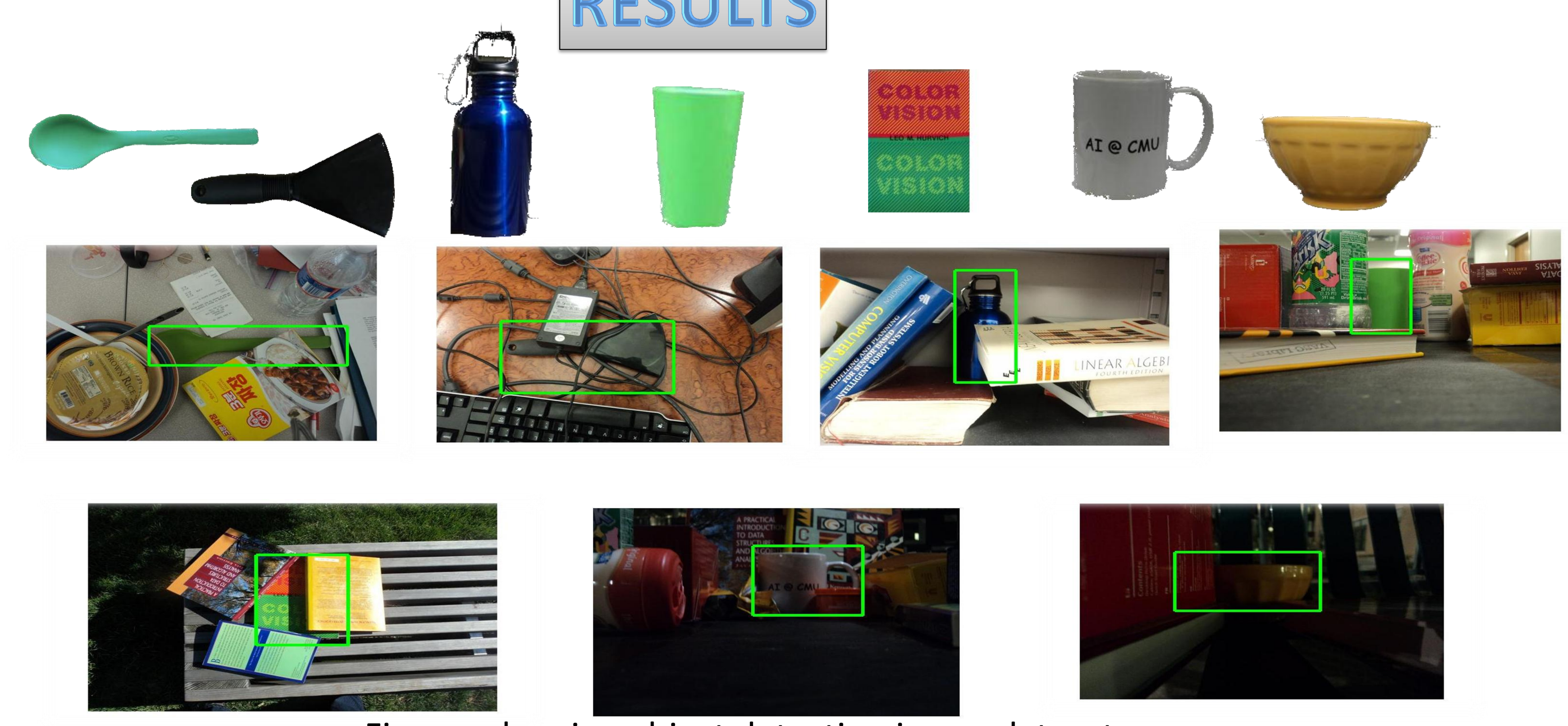


Figure showing detection points after running mean shift on distance score map

An object is correctly detected if the intersection over-union (**IoU**) of the predicted bounding box and the ground truth bounding box is greater than 0.5. → Then we take 95 % of sorted true positive value as threshold. → Then we run Rline2D on the cells which has scores more than the thresholds

RESULTS

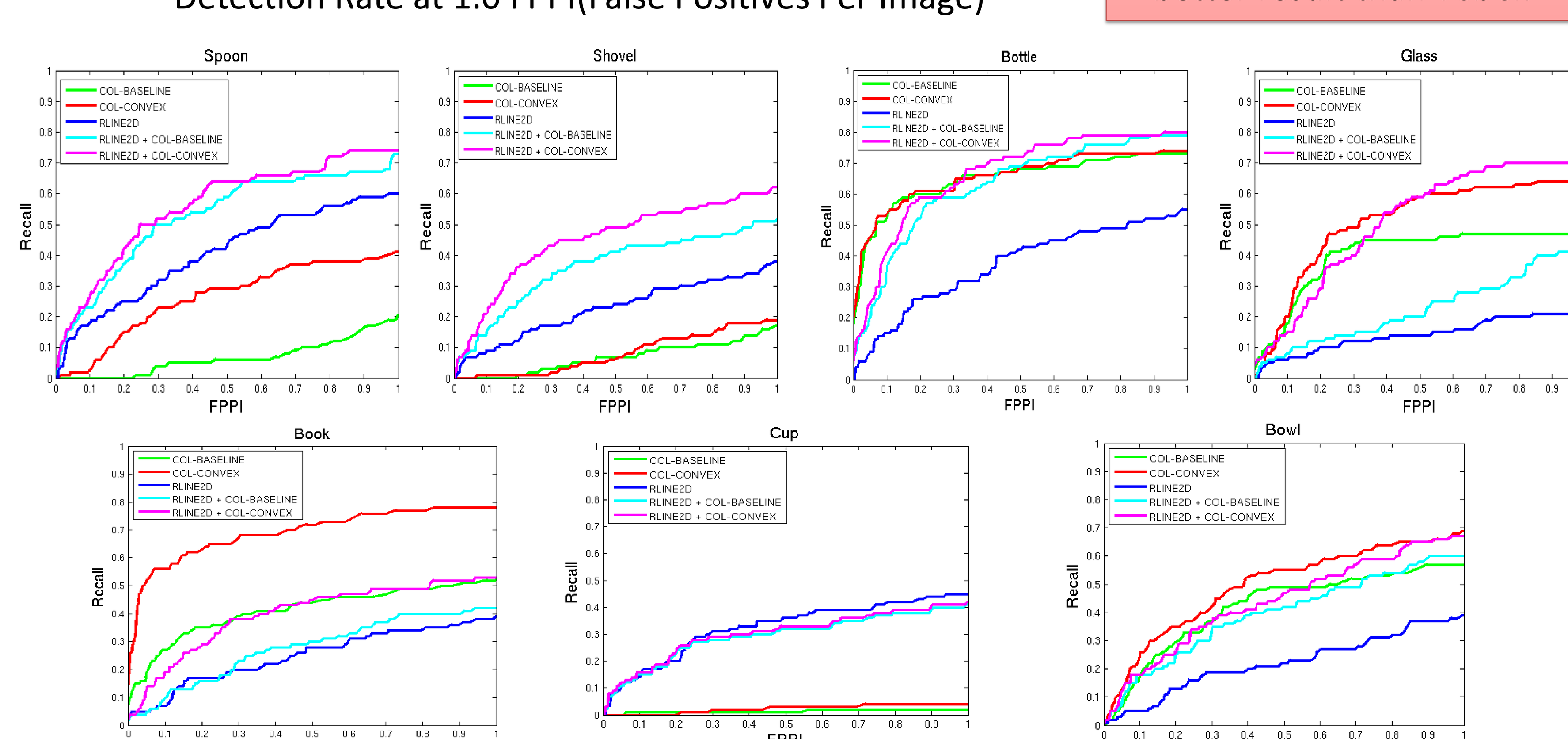


Figures showing object detection in our dataset

	Color Baseline	Color Convex	Rline2D	Color Baseline +Rline2D	Color Convex +Rline2D
Spoon	0.21	0.41	0.60	0.73	0.74
Shovel	0.17	0.19	0.38	0.51	0.62
Bottle	0.73	0.74	0.55	0.79	0.80
Glass	0.49	0.65	0.24	0.41	0.73
Book	0.52	0.78	0.39	0.42	0.53
Cup	0.02	0.04	0.45	0.41	0.42
Bowl	0.57	0.69	0.39	0.60	0.67
Average	**0.39**	**0.50**	**0.43**	**0.55**	**0.64**

Detection Rate at 1.0 FPPI(False Positives Per Image)

- There are 700 images in the dataset , 100 for each object. For evaluation of each object we ran our algorithm for all 700 images.
- In baseline, we compute the Euclidian distance from average color of each cell instead of convex hull corresponding to each cell.
- All the results are taken in RGB color space. Also we found that RGB gave the better result than YCbCr.



FPPI/Recall curve for various objects

CONCLUSION AND FUTURE WORK

- Color Convex always give better results than the color baseline. Also combining it with Rline2D gave boost in the results in most of the cases.
- Color model didn't perform well for white color cup and black color shovel because in dataset lot of images have white and black color background. Rline2D didn't perform well for bowl , glass and book as they are very common shapes in dataset , so many FPs
- In future, we are going to analyze the result by using HOG detector instead of Rline2D.
- Also images are in uniform illumination, the color transformation matrix should be consistent . In future we will try to give some weight to transformation matrix consistency

REFERENCES AND ACKNOWLEDGEMENT

1. Kobus Barnard .Modeling Scene Illumination Colour for Computer Vision and Image Reproduction: A survey of computational approaches.
2. E. Hsiao and M. Hebert. Occlusion reasoning for object detection under arbitrary viewpoint. In CVPR, 2012.
3. Thanks to my advisors Edward Hsiao and Prof. Martial Hebert for their valuable guidance