

Deep ChArUco: Dark ChArUco Marker Pose Estimation Danying Hu, Daniel DeTone, Vikram Chauhan, Igor Spivak and Tomasz Malisiewicz Magic Leap, Inc.

Introduction

In this paper, we present **Deep ChArUco**:

- A deep convolutional neural network system trained to be accurate and robust for ChArUco marker detection under extreme lighting and motion and a neural network for subpixel corner refinement
- A novel training dataset collection recipe involving autolabeling images and synthetic data generation.

Network Architecture



Figure 1: Two-Headed ChArUcoNet and RefineNet. Both ChArUcoNet and **RefineNet** are SuperPoint-like [1] networks using VGG-based backbone:

- ChArUcoNet: One of the network heads detects 2D locations of ChArUco board's corners and the second head classifies them.
- RefineNet: takes a 24×24 image patch and outputs a single subpixel corner location at 8× the resolution of the central 8×8 region.

Training ChArUcoNet **Data generation (see Figure 2)** Data augmentation with synthetics effects:

• blur (gaussian, motion, speckle) • lighting • homographic transform

[1] D. DeTone, T. Malisiewicz, and A. Rabinovich, "Superpoint: Self-supervised interest point detection and description," in CVPR Deep Learning for Visual SLAM Workshop, 2018. [Online]. Available: http://arxiv.org/abs/1712.07629





good lighting lighting change Figure 2: Training data collection



Training RefineNet







dataset, before and after data augmentation.

Figure 4: Examples of synthetic training patches. Each image is 24×24 pixels and contains one a ground-truth corner within the central 8×8 pixel region.

Evaluation on real video sequences



Figure 7: Detector performance comparison under extreme shadows (top) and motion (bottom).



Conclusion

This work demonstrates that deep convolutional neural networks can dramatically improve the detection rate for ChArUco markers in lowlight, high-motion scenarios where the traditional ChArUco marker detection tools often fail. We have shown that our Deep ChArUco system, a combination of ChArUcoNet and RefineNet, is significantly more robust to adverse effects such as illumination, blur, and shadows.



LONG BEACH CALIFORNIA June 16-20, 2019

Video	deep acc	cv acc	deep ϵ_{re}	$\mathbf{cv} \ \epsilon_{re}$
0.31ux	100	0	0.427 (0.858)	nan
0.31ux	100	0	0.388 (0.843)	nan
1lux	100	0	0.191 (0.893)	nan
1lux	100	0	0.195 (0.913)	nan
$\overline{3lux}$	100^{-1}	$\overline{100}$	0.098 (0.674)	$\left[\overline{0.168}\right]$
3lux	100	100	0.097 (0.684)	0.164
5lux	100	100	0.087 (0.723)	0.137
5lux	100	100	0.091 (0.722)	0.132
101ux	100	100	0.098 (0.721)	0.106
10lux	100	100	0.097 (0.738)	0.105
30lux	100	100	0.100 (0.860)	0.092
30lux	100	100	0.100 (0.817)	0.088
50lux	100	100	0.103 (0.736)	0.101
50lux	100	100	0.102 (0.757)	0.099
100lux	100	100	0.121 (0.801)	0.107
100lux	100	100	0.100 (0.775)	0.118
4001ux	100	100	0.086 (0.775)	0.093
4001ux	100	100	0.085 (0.750)	0.093
700lux	100	100	0.102 (0.602)	0.116
700lux	100	100	0.107 (0.610)	0.120
shadow 1	100^{-1}	42.0	0.254(0.612)	$\overline{0.122}$
shadow 2	100	30.1	0.284 (0.618)	0.130
shadow 3	100	36.9	0.285 (0.612)	0.141
motion 1	74. 1	16.3	1.591 (0.786)	$\bar{0.154}$
motion 2	78.8	32.1	1.347 (0.788)	0.160
motion 3	80.3	31.1	1.347 (0.795)	0.147

Table 1: Individual test video summary of the pose detection rate(percentage of frames with reprojection error less than 3 pixels) as well as the mean reprojection error.