Reproduction Angular Error: An Improved Performance Metric for Illuminant Estimation

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Illuminant Estimation which is the process of estimating the colour of the prevailing light and discounting it from the image is often done as the preprocessing step in computer vision, so that the image colour be used as a stable cue for indexing, recognition, tracking, etc. [4, 5].

Almost all illumination estimation research uses the angle between the RGB of the actual measured illuminant colour and that estimated one as the recovery error, which is defined as:

$$err_{recovery} = \cos^{-1}\left(\frac{(\underline{\rho}^{E} \cdot \underline{\rho}^{Est})}{\|\underline{\rho}^{E}\|\|\underline{\rho}^{Est}\|}\right) \tag{1}$$

where $\underline{\rho}^{E}$ denotes the RGB of the actual measured light, $\underline{\rho}^{Est}$ denotes the RGB estimated by an illuminant estimation algorithm and '.' denotes the vector dot product. Over a benchmark set, the average angular performance is calculated (including mean, median, and quantiles) and different algorithms are ranked according to these summary statistics [3].

This paper argues that recovery angular error despite its wide spread adoption has a fundamental weakness which casts doubt on its suitability. We observe that the same scene, viewed under two different coloured lights, leads to different recovery errors for the same illuminant estimation algorithm, despite the fact that when we remove the colour bias due to illuminant (we divide out by light) exactly the same reproduction is produced.

To illustrate this point we show at the top of Figure 1 four images of the same scene from the SFU Lab dataset [1] which are captured under different chromatic lights, from left to right: solux-4700K+blue filter; Sylvania warm white fluorescent; solux-4700K+3202+blue filter and Philips Ultralume fluorescent. Notice how much the colour (due to illumination) varies from left to right. Now, using the simple gray-world algorithm [2] for illuminant estimation we estimate the RGB of the light (the average image colour is the estimated colour of the light). Dividing the images by this estimate we produce the image outputs shown in the second row. In this case gray-world works reasonably well and the object colours look correct (though, of course this is not always the case). It is easy to show that dividing out by the gray-world estimate (or, indeed the estimates made by most algorithms) that the **same** output reproduction is made. In the 3rd row of Figure 1 we show the recovery angular errors (the plot with open bullets). Even though the same reproduction is produced the recovery angular error varies from 5.5° to 9° (an 80% difference).

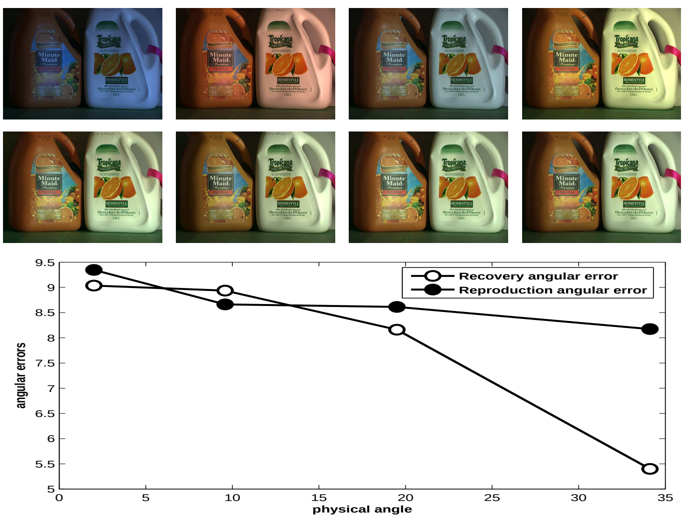

Figure 1: Row 1: four images captured under very chromatic illuminants. Row 2: corrected images using general gray-world [2] algorithm (Images are from [1]). Row 3: The Recovery angular error (conventional error measure) versus the Reproduction angular error (proposed error measure).

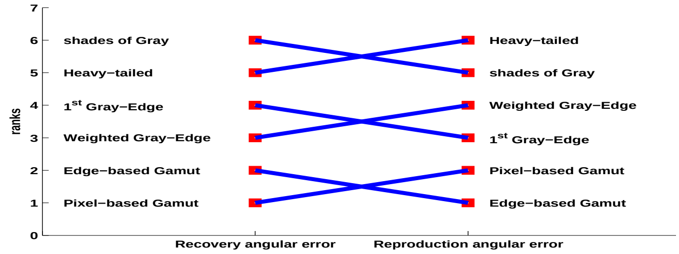

Figure 2: A pictorial scheme of the changed rank algorithms for SFU dataset [1] based on both median recovery and reproduction angular errors.

We begin this paper by quantifying the scale of this problem. For a given scene and algorithm, we solve for the range of recovery angular errors that can be observed given all colours of light. We define a theory which states that the lowest errors are for red, green and blue lights and the largest for cyans, magentas and yellows.

In the second part of the paper, we propose a new *reproduction angular error* which is defined as the angle between the RGB of a white surface when the ground-truth ($\underline{\rho}^{E,W}$ in Eq. (2)) and estimated illuminations ($\underline{\rho}^{Est}$ in Eq. (2)) are 'divided out' :

$$err_{reproduction} = \cos^{-1}\left(\frac{(\underline{\rho}^{E,W}/\underline{\rho}^{Est}).\underline{U}}{|(\underline{\rho}^{E,W}/\underline{\rho}^{Est})|\sqrt{(3)}}\right), \quad \underline{U} = \frac{\underline{\rho}^{E,W}}{\underline{\rho}^{E,W}} \tag{2}$$

We prove that this reproduction error metric, by construction, gives the same error for the same algorithm-scene pair. The reproduction angular errors for the reproduced images in Figure 1 are shown in the 3rd row of the same figure (the plot with the black bullets). Compared to the recovery angular error, the reproduction error is almost similar for the same scene captured under different colours of illuminants (almost since the process of image formation does not only depend on the color of the illuminant).

For many algorithms and many benchmark datasets we recompute the illuminant estimation performance of a range of algorithms for the new reproduction error and then compare against the algorithm rankings for the old recovery error. We find that using the new measure, the rankings of algorithms remains, while broadly unchanged can change and there can be local switches in rank (see Figure 2). Also the algorithm parameters which can be tuned to provide that best illuminant estimation performance can be chosen differently, depending on whether the reproduction angular error or the recovery angular error is used for evaluation.

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