HUE VARIANCE PREDICTION An Empirical Estimate of the Variance within the Hue of an Image

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Keywords: Hue noise, image processing, illumination invariance.

Abstract: In the area of vision-based local environment mapping, inconsistent lighting can interfere with a robust system. The HLS colour model can be useful when working with varying illumination as it tries to separate illumination levels from hue. This means that using hue information can result in an image invariant to illumination. This can be valuable when trying to determine object boundaries, object identification and image correspondence. The problem is that noise is greater at lower illumination levels. While removing the illumination effects on the image, separating out hue means that the noise effects of non-optimal illumination remain. This paper looks at how the known illumination information of pixels can be used to accurately predict and reduce noise in the hue obtained in video from a colour digital camera.

1 INTRODUCTION

With vision-based local environment mapping consistency in the environment is highly desirable. This includes consistent lighting conditions which means that most research is conducted under as controlled an environment as possible. Unfortunately this is not a luxury that can be afforded in real world applications which means that many projects can not achieve widespread public use. The problem is that illumination in general usage is unpredictable, causing tasks such as colour tracking for object recognition to be problematic because the intrinsic characteristics of digital cameras causes the value of hue to vary with illumination. There have been projects in the past that have tried to track the colour of an object as it changes with varying levels of success (Grant and Green, 2004)(Nummiaro et al., 2002)(Vergs-Llah et al., 2001) shown in figure 1. While these methods can work, they often need to be reinitialised if tracking is lost and are computationally inefficient leaving less for the primary vision application.

This research takes the approach of an illumination invariant filter on video data, acquiring video frames and converting them into a normalised illumination format consisting of the raw colours of the N. Grant R., D. Green R. and J. Clark A. (2007).

Figure 1: Frames from a dynamic colour tracker (Grant and Green, 2004).

scene. Conversion to the HLS colour model shown in figure 2 is the starting point to this transformation as the hue component of this colour model is essentially the colour of an object with the illumination intensity information stripped out. White balancing is also necessary to remove light source colouring effects on objects.

This would be an ideal illumination invariant input for a computer vision system as with accurate white

In Proceedings of the Second International Conference on Computer Vision Theory and Applications - IFP/IA, pages 5-9 Copyright (C) SciTePress

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correct the effects of discoloured lighting in an image (Lam et al., 2004).

By implementing reliable white balancing and using an invariant colour model an object's colour should rarely change due to illumination changes. Unfortunately this is not the case when the intensity of light reflected from an object nears the outer limits of the camera's visible range. Cameras are not sensitive to these areas and so noise causes the colour/hue of an object to vary dramatically.



Figure 4: Shadow segmentation using an invariant colour model (Salvador et al., 2001).

3 EXPERIMENTATION

3.1 Method

The following experiment aims to discover the correlation between the effect of noise levels on hue and the levels of the other two components of HLS colour (luminance and saturation). These may be useful predictors as they represent the amounts of light coming into the camera and an indication of the accuracy of hue. A predictable correlation between these two factors enables countering these noise effects.

Different scenes were selected for range of colour and brightness. The camera exposure period was up to 30 seconds at a frame rate of approximately 15fps to collect accurate HLS colour information for each pixel of the scene over time. Each pixel was classified by means of averaging to a specific luminance and saturation pair. Standard deviation of the hue values collected were calculated for each pixel. Hue variances are added to an array of minimum hue variance for each luminance by saturation pair (256x256).

3.2 Results

Figure 5(a) shows the data extracted from this experiment. It can be seen that at low and high luminance and low saturation values with results indicating that the amount of noise in hue can spike significantly. There are also some scattered hue noise peaks in the data as can be seen in the graph. These can be attributed to other effects caused by the method of data collection. With a near stationary camera, tiny movements can cause large changes in pixel colour near the edges of objects. Because of this the lowest variance is always selected when duplicate luminance and saturation pairs arise, this helps reduce these effects.

These results suggest that it is possible to correctly predict the noise of a pixel without any temporal information. Luminance and saturation may therefore be accurate predictors of the hue variance for any given pixel.

3.3 Curve Fitting

From the data found in figure 5(a) we can see that, with the correct formula, hue variation can be predicted. The problem is finding this fitting a mathematical curve to this data. By analysing a cross section of the data along one axis at a time, it was found that both axes closely fit an inverse squared curve which when multiplied together produced a close fit to the data. In the case of the luminance direction the symmetry means the term L is inverted half way.

When L < 128:

$$H = \left(\frac{\alpha}{S^2} + \beta\right) \times \left(\frac{\gamma}{L^2} + \delta\right) \tag{1}$$

Else:

$$H = \left(\frac{\alpha}{S^2} + \beta\right) \times \left(\frac{\gamma}{(255 - L)^2} + \delta\right) \tag{2}$$

To match the data from the previous experiment, the coefficients found to be a close fit were: $\alpha = 2913$, $\beta = 1.18$, $\gamma = 1974$, $\delta = 0.6301$. This produces the predicted graph in figure 5(b). These coefficients would be different for different cameras but the equation should still be the same. Each camera would need to be calibrated for a specific noise curve.

3.4 Application

Figure 6 shows the different stages of this being applied to a frame of video beginning with figure 6(a).

Figure 6(b) shows the image with only the hue component remaining, this was done by converting to HLS then setting luminance to 128 and saturation to 255 and then converting it back into the RGB colour space. Figure 6(c) is formed by applying the equations 1 and 2 to the luminance and saturation from the original image. This is then combined with the hue image to form the image shown in figure 6(d). This image gives an indication as to how reliable the colour data is and gives us an ideal entry into noise reduction, edge detection, frame correlation or object segmentation algorithms.

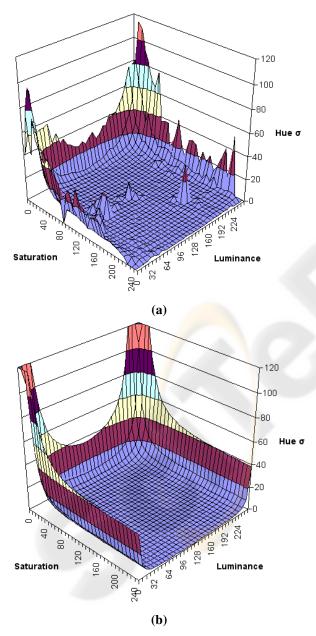
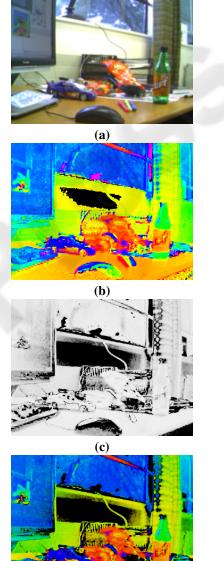


Figure 5: Hue standard deviation vs. Saturation and Luminance (a) Experimental results (b) Predicted curve.



(**d**)

Figure 6: (a) Original image (b) Hue image (c) Predicted hue noise image (d) Hue image with darkened noisy areas.

4 CONCLUSIONS

This research is working towards creating an illumination invariance filter for colour camera input. This can be used to better identify or correlate objects regardless of changes in lighting conditions or viewing angle. While white balancing and illumination invariant colour models are on the way to achieving this, they come across large amounts of noise when trying to identify colours that have intensities outside of the sensitive range of the camera. This research has remedied this by showing that an equation can be used to predict how reliable colour values are across an image. In this way correlation between a persistent representation and the camera input can be made more reliably.

5 FUTURE WORK

Now with colour error being accurately predicted in video, further applications of this research can take into account this noise and operate more robustly for it. The current two directions of research following on from this are image enhancement and frame correlation. Using the overlaps of variance for neighbouring pixels, a pixels colour and variance estimates are narrowed to become more accurate. This means slight variations in colour across an object due to camera noise are minimised resulting in a cleaner image for viewing or vision systems. Frame correlation becomes simpler as the computed variance of the pixel will generally encompass the detected colour of same physical point in following frames.

REFERENCES

- Fintzel, K., Bendahan, R., Vestri, C., Bougnoux, S., Yamamoto, S., and Kakinami, T. (2003). 3d vision system for vehicles. In *Intelligent Vehicles Symposium*, 2003. Proceedings. IEEE, pages 174–179.
- Grant, R. N. and Green, R. D. (2004). Tracking colour movement through colour space for real time human motion capture to drive an avatar. In *Proceedings of Image and Vision Computing New Zealand*.
- Lam, H.-K., Au, O. C., and Wong, C.-W. (2004). Automatic white balancing using standard deviation of rgb components. In *International Symposium on Circuits and Systems*, volume 3, pages 921–924.
- Nummiaro, K., Koller-Meier, E., and Gool, L. J. V. (2002). Object tracking with an adaptive color-based particle filter. In Annual Symposium of the German Association for Pattern Recognition, page 353 ff.

- Salvador, E., Cavallaro, A., and Ebrahimi, T. (2001). Shadow identification and classification using invariant color models. In *IEEE International Conference* on Acoustics, Speech, and Signal Processing, volume 3, pages 1545–1548.
- Takeno, J. and Hachiyama, S. (1992). A collision-avoidance robot mounting ldm stereo vision. In Proceedings of the IEEE International Conference on Robotics and Automation, 1992., volume 2, pages 1740–1752.
- Tsuji, T., Hattori, H., Watanabe, M., and Nagaoka, N. (2002). Development of night-vision system. In *IEEE Transactions on Intelligent Transportation Systems*, volume 3, pages 203–209.
- Vergs-Llah, J., Aranda, J., and Sanfeliu, A. (2001). Object tracking system using colour histograms. In Proceedings of the 9th Spanish Symposium on Pattern Recognition and Image Analysis, pages 225–230.
- Wang, J. M., Chung, Y. C., Chang, C. L., and Chen, S. W. (2004). Shadow detection and removal for traffic images. In *IEEE International Conference on Networking, Sensing and Control*, volume 1, pages 649–654.
- Yao, J. and Zhang, Z. (2004). Systematic static shadow detection. In *International Conference on IPattern Recognition*, volume 2, pages 76–79.