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Enhancement of Scenery and Digital Camera Images by using Entropy Estimators

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Abstract: *The colors present in an image of a scene provide information about its constituent elements. But the amount of information depends on the imaging conditions and on how information is calculated. This work had two aims. The first was to derive explicitly estimators of the information available and the information retrieved from the color values at each point in images of a scene under different illuminations. The second was to apply these estimators to simulations of images obtained with five sets of sensors used in digital cameras and with the cone photoreceptors of the human eye. Estimates were obtained for 50 hyper spectral images of natural scenes under daylight illuminants with correlated color temperatures 4,000, 6, 500, and 25,000K. Depending on the sensor set, the mean estimated information available across images with the largest illumination difference varied from 15.5 to 18.0 bits and the mean estimated information retrieved after optimal linear processing varied from 13.2 to 15.5 bits (each about 85 percent of the corresponding information available). With the best sensor set, 390 percent more points could be identified per scene than with the worst. Capturing scene information from image colors depends crucially on the choice of camera sensors.*

Keywords: *color vision, color information, digital color cameras, color processing, information theory, natural scenes, kth nearest neighbour statistics, color constancy.*

1. INTRODUCTION

Color provides information about the reflecting properties of surfaces, thereby allowing regions of a scene to be demarcated and the elements of regions to be distinguished. More specifically,if images of a scene under a particular illumination are obtained with a digital tri chromatic camera. A priori, it seems unlikely that all the elements in a scene can be characterized in this way. One problem is that the color values at each point in an image depend on the spectrum of the illumination on the scene, so that when the illumination changes, so generally do the colour values. This confounding effect of illumination can be largely discounted by correcting colour values by so-called Von Kries scaling although not completely. Another problem is that different reflectance spectra at different points in the scene under the same illumination can produce the same colour values. This is the phenomenon of mesmerism and is a consequence of the number of degrees of freedom in natural reflectance spectra being greater than the number of degrees of free domain color values, namely, three with a tri chromatic camera. Nevertheless, there remains a strong dependency between the color values of different images of the same scene under different illuminations.

2. EXISTING SYSTEM

The information available from the color values at each point in the scene imaged under different illuminations and the information retrieved in the basic task of matching points across those images by their color values. The information available is, by construction founded on a theoretical camera with an infinite number of pixels. It sets, therefore, an upper (finite) bound on the information actually available from any camera with a finite number of pixels, which can yield only a finite sample of color values. The information available necessarily depends on factors such as the spectral reflectances of the surfaces in the scene and their relative abundances, the spectral radiances of the illuminations on the scene, and the spectral sensitivities of the camera sensors. The information retrieved depends not only on these factors, but also on how the sensor signals are processed and then matched, for example, by von Kries scaling and by nearest neighbour matching. The information available is also an upper bound on the information retrieved.

2.1 Draw Backs

The drawbacks of the existing system are

1. The color values of different images of the same scene under different illuminations. This dependency can be quantified with Shannon’s mutual information.
2. A priori, it seems unlikely that all the elements in a scene can be characterize this way. One problem is that the color values at each point in an image depend on the spectrum of the illumination on the scene, so that when the illumination changes, so generally do the color values.

3. Proposed System

The conditional must be known or estimated reliably, which is not generally feasible. Instead, a nearest-neighbour criterion may be used, which may not be optimal, but may approach optimality with a judiciously chosen metric. The information retrieved is then the logarithm of the maximum number of distinct points that can be reliably identified by nearest-neighbour matching across two images of a scene under different illuminates. It is always lower than or equal to the information available. An equivalent definition of information retrieved in the more general. By contrast with the information available, invertible transformations of the sample values can increase the information retrieved. a theoretical observer making nearest-neighbour matches across two images of a scene under different illuminates. A slightly different interpretation of that estimator can be derived from the relationship between the minimum number of bits needed to encode a random variable and the entropy of that variable Without any prior information, the number of bits needed to encode a sample of N points from an image of a scene with color values t_1a_{1i} under illuminate the entropy of a random variable with a discrete uniform distribution.

3.1 Sensor Signals and Image Entropy

Consider a scene illuminated by a spatially uniform global illuminate with incident spectral radiance $e(\lambda)$ at wavelength λ. Suppose that at a point (x, y) in the scene the effective spectral reflectence is $\rho(\lambda;\ x,\ y)$ so that the reflected spectral radiance is given by $c\ \lambda;\ x,\ y\ = e\ \lambda\ \rho\ \lambda;\ x,\ y$. Suppose that this reflected spectrum is sampled by the long-medium and short wavelength sensitive (conventionally, R,and B) sensors of a digital camera (or one photoreceptors of the eye) with spectral sensitivities $S_R(\lambda)$, $S_G(\lambda)$, and $S_B(\lambda)$,respectively. The corresponding triplet of color values (r,g,b) at (x,y) encodes the spectrum $c(\lambda;\ x,\ y)$ thus

$$
\begin{aligned}
r &= \int s_R\ \lambda\ \ c\ \lambda;\ x,\ y\ \ d\lambda, \\
g &= \int s_G\ \lambda\ \ c\ \lambda;\ x,\ y\ \ d\lambda, \\
b &= \int s_B\ \lambda\ \ c\ \lambda;\ x,\ y\ \ d\lambda,
\end{aligned}
\qquad 1
$$

where the integral is evaluated over the visible wavelength range. If the point (x, y) within the scene is chosen randomly, the color values r,g and b in (5.1) may be treated as instances of continuous random variables, R, G and B. The triplet a=(r,g,b) is an instance of a tri variant continuous random variable A=(R,G,B). whose probability density function (pdf) is f. This pdf characterizes the nature of the unpredictability of the color values for a particular scene, illuminate and set of sensors.

A discredited version of the continuous random variable A can be obtained by partitioning the space in which the (bounded) variables R, G, and B take their values. Suppose that the partition has a finite number of bins, D say, indexed by an integer d with $1 \le d \le D$. Suppose that each bin has equal edge lengths $\Delta r = \Delta g = \Delta b$, and let $\Delta a = \Delta r \Delta g \Delta b$. For each d, let a_d be the value of a within the d_{th} ,b_{in} such that

$$f(a_d)\Delta a = \int_{r_d}^{(r_d+\Delta r_d)} \int_{g_d}^{(g_d+\Delta g_d)} \int_{b_d}^{(b_d+\Delta b_d)} f(r,g,b)\,dr\,dg\,db \qquad (2)$$

Denote by $A^{\Delta} = (R^{\Delta}, G^{\Delta}, B^{\Delta})$ the discretized version of A whose probability mass function (pmf) p is given by

$$p(a_d) = P\{A^{\Delta} = a_d\} = f(a_d)\Delta a, \text{for d=1,………,D} \qquad (3)$$

The entropy H (A^{Δ}) of the discrete random variable A^{Δ} for a particular scene, illuminate and set of sensors is then defined by

$$H(A^{\Delta}) = -\sum_{d=1}^{D} p(a_d)\log p(a_d), \qquad (4)$$

where the probabilities p(ad) are given by (5.3) and where conventionally 0 log 0 = 0. The entropy (A^{Δ}) ranges from zero to log D. If the logarithm is to the base 2, then the entropy is in bits, if it is the natural logarithm, then the entropy is in nats.

If all the points in a scene have the same color value, so that the pmf

$p(a_d)$ of A^{Δ} is zero except at one particular value of d e.g., if the scene is a perfectly homogeneous surface so that all the points have the same effective reflectance spectrum or if the binning is too coarse(i.e., D is too small) to capture the differences is effective spectral reflectance between points, then there is no uncertainty about the color value at any chosen point and $H(A^{\Delta}) = 0$. Conversely, if all the points in a scene have different color values, so that the pmf of A^{Δ} is uniform, i.e., p(ad) = 1/D for all d=1,………, D then the uncertainty about the color value of the chosen point is maximum and $H(A^{\Delta}) = \log D$.

3.2 Information Available and its Estimators

The four estimators were used to estimate the information available:

(a) A kernel Density Estimator

(b) A generalized version of a nearest-neighbour estimator due to kozachenko and Leonenko estimator

(c) A nearest neighbour estimator due to kraskov,stogbauer and grassberger

(d) And an experimental offset modification used to improve both estimators (a) and (b)

3.3 Offset Estimators

The foregoing estimators were found to converge slowly with gaussian images. To improve the convergence of the kernel density estimator and Kozachenko-Leonenko estimator each was decomposed into two components: one, the mutual information between equivalent Gaussian variables with known variance-covariance structure, the other, an offset obtained by applying the estimator to normalized versions of A_1, A_2, and A_{12}. This decomposition was not possible with the Kraskov-StÖgbauer-Grassberger estimator $\hat{I}_{KSG}(A_1; A_2)$ which estimates mutual information directly.

If A is a random variable and t an invertible linear transformation is

$$h(A) = h(tA) - \log|t|, \qquad (5)$$

Where $|t|$ is the absolute value of the determinant matrix representing t.Set $t_1 = (VarA_1)^{-1/2}$ and $t_2 = (VarA_2)^{-1/2}$ and $t_{12} = (VarA_{12})^{-1/2}$ let I_{EG} (A_1; A2) be the mutual information of the equivalent Gaussian variables, i.e., having the same variance-covariance structure as A_1 and A_2, so that

$$I_{EG}(A_1;A_2)=\frac{1}{2}\log(\frac{|VarA_1||VarA_2|}{|VarA_{12}|}). \tag{6}$$

The mutual information between A_1 and A_2 can be written as

$$I(A_1;A_2)=I_{EG}(A_1;A_2)+h(t_1A_1)+h(t_2A_2)-h(t_{12}A_{12}). \tag{7}$$

3.4 Information Retrieved and its Estimators

There are two estimators to retrieve the information they are:

1. Nearest Neighbour Errors and Entropy of Point Matching
2. Grassberger Estimator

3.5 Nearest Neighbour Errors and Entropy of Point Matching

The estimator of the information retrieved that was developed based on the entropy of the error of a theoretical observer making nearest neighbour matches across two images of a scene under different illuminations. A slightly different interpretation of that estimator can be derived from the relationship between the minimum number of bits needed to encode a random variable and the entropy of that variable. The entropy of that random variable,

$$H(M)=-\sum_{m=0}^{N-1} p_m \log p_m, \tag{8}$$

is the entropy of point matching. It yields the number of bits needed to encode the N surfaces in an image of a scene under illumination e_1 given an image of the same scene under illuminante$_2$. If matching is perfect, so there are no incorrect matches for any point, then H(M)=0. Conversely, if matching is uniformly random, then H(M)=logN.

The difference logN-H(M) is the reduction in number of bists needed to encode the N points in an image of a scene under illumination e_1 given an image of the same scene under illumination e_2. An estimator of information retrieved by nearest neighbour matching I_{NN} $(t_1A_1;\ t_2A_2)$ is defined precisely by that difference. That is,

$$I_{NN}(t_1A_1;t_2A_2)=\log N - H(M) \tag{9}$$

3.6 Grassberger Estimator

The naive estimator of the entropy H(M) is usually biased when the number of nonzero probabilities p_m is close to the sample size N, and a bias corrected estimator due to Grassberger was therefore was used in this analysis. If φdenotes the digamma function, the Grassberger estimator $\hat{H}_G(M)$ of H (M) is defined in nats by

$$\hat{H}_G(M)=\ln N-\sum_{m=0}^{N-1} p_m \psi(Np_m) \tag{10}$$

The Grassberger estimator $\hat{I}_{NNG}$ $(t_1A_1;\ t_2A_2)$ of the information retrieves is accordingly,

$$\hat{I}_{NNG}(t_1A_1;t_2A_2)=\log N-\hat{H}_G(M). \tag{11}$$

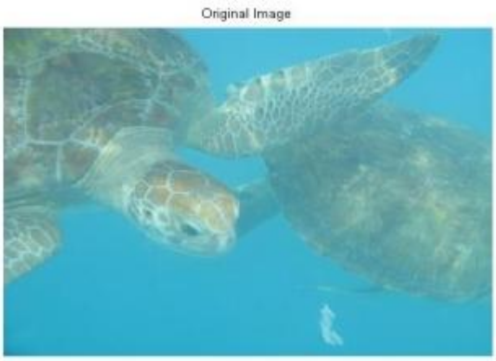
3.7 Advantages and Applications

The advantages of proposed system are

- NN is very simple to understand and easy to implement.
- Because the process is transparent, it is easy to implement and debug.
- In situations where an explanation of the output of the classifier is useful,
- NN can be very effective if an analysis of the neighbours is useful as explanation.
- Case-Retrieval Nets are an elaboration of the Memory-Based Classifier idea that can greatly improve run-time performance on large case-bases.

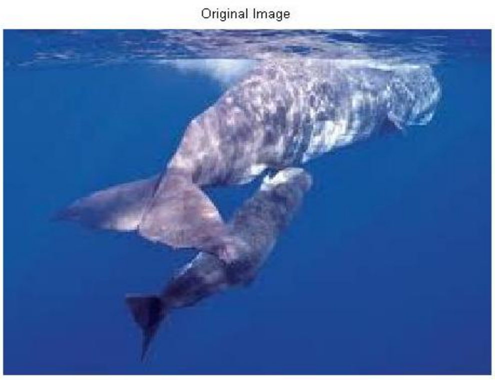
Some of the applications are automatic surveillance, behaviour analysis, automatic analysis of human motion in videos.

4. Results and Discussions



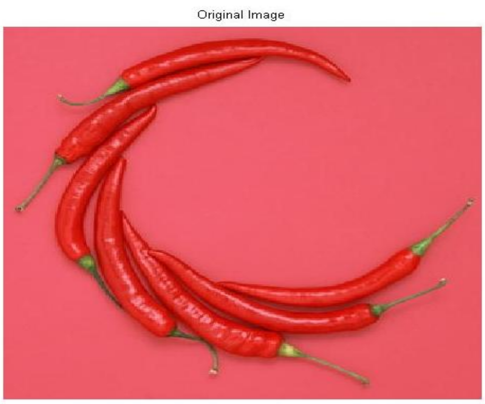
Original Image

Nearest Neighbour Grassberger Image



Original Image

Nearest Neighbour Grassberger Image



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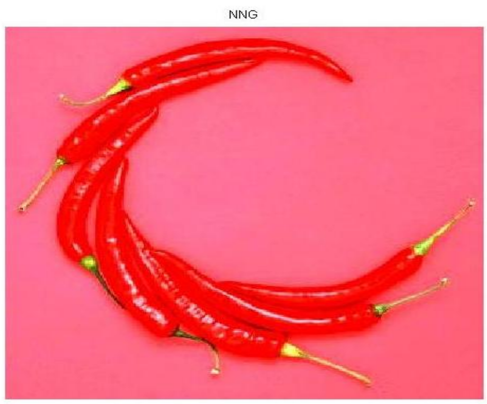

Nearest Neighbour Grassberger Image

5. Conclusion

Capturing scene information from image colors depends crucially on the choice of camera sensors. Although not all of the information available can be retrieved with any particular set of sensors, providing that the sensor spectral sensitivities are optimally modified with a sharpening transformation, the information retrieved can approach the information available, depending of course on the scene and illumination. As shown in this work, estimating the continuous and discrete informational quantities involved and comparing them over different sets of camera sensors is not straight forward, but clear differences between sensor sets did emerge over a range of natural scenes and daylight illuminates. Most notably, with the best sensor set about 390 percent more points could be identified per scene than with the worst.

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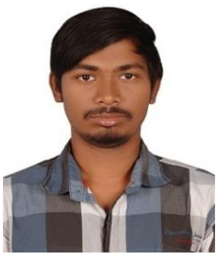
K.Ayyana completed his Master`s Degree in Telematics & Signal Processing from National Institute of Technology Rourkela and presently working as an Assistant Professor in Brindavan Institute of Technology & Science, Kurnool A.P. His areas of interests are Signal Processing, Image Processing and Communication systems.



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